MODERNIZING LEARNING

Building the Future Learning Ecosystem

J.J. Walcutt and Sae Schatz

Advanced Distributed Learning Initiative
and more than 85 contributors

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Education is the answer to everything. It’s the door opener; it opens your mind to the possible.

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FOUNDATIONS

TECHNOLOGY

ACRONYMS

ADDIE	Analyze, Design, Develop, Implement, and Evaluate
ADKAR	Awareness, Desire, Knowledge, Ability, Reinforcement
ADL	Advanced Distributed Learning
AI	Artificial Intelligence
API	Application Programming Interface
AR	Augmented Reality
ASVAB	Armed Services Vocational Aptitude Battery
BYOD	Bring Your Own Device
cMOOC	Connectivist Massive Open Online Course
CORDRA	Content Object Repository Registration/Resolution Architecture
DARPA	Defense Advanced Research Projects Agency
DHS	Department of Homeland Security
DIS	Distributed Interactive Simulation
DoD	Department of Defense
EEG	Electroencephalogram
EMT	Emergency Medical Technician
ESSA	Every Student Succeeds Act
FAA	Federal Aviation Administration
FATE	Fairness, Accountability, Transparency, and Ethics
FERPA	Family Educational Rights and Privacy Act
FM	Field Manual
fMRI	Functional Magnetic Resonance Imaging
FYI	For Your Information
GIFT	Generalized Intelligent Framework for Tutoring
HLA	High-Level Architecture
HR	Human Resources
HSI	Human–Systems Integration
HTML	Hypertext Markup Language
HTTP	Hypertext Transfer Protocol
I/ITSEC	Interservice/Industry Training, Simulation and Education Conference
ICAP	Interactive, Collaborative, Active, and Passive
ICICLE	Industry Connections Industry Consortium on Learning Engineering
IDS	Intrusion Detection System
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IEEE-SA	IEEE Standards Association
InKD	Industrial Knowledge Design
IoT	Internet of Things
IPS	Intrusion Prevention System
ISD	Instructional Systems Design
ISO	International Standards Organization
IT	Information Technology

K-12	Kindergarten through 12th Grade
KPI	Key Performance Indicator
LMS	Learning Management System
LOM	Learning Object Metadata
LRMI	Learning Resource Metadata Initiative
LRS	Learning Record Store
LX	Learning Experience
LXD	Learning Experience Design
MERLOT	Multimedia Education Resource for Learning and Online Teaching
MOOC	Massive Open Online Course
MSSP	Managed Security Services Provider
NASA	National Aeronautics and Space Administration
NGO	Non-Governmental Organization
NYCRR	New York Codes, Rules and Regulations
OECD	Organisation for Economic Co-operation and Development
OER	Open Educational Resources
OPM	Office of Personnel Management
PERLS	PERvasive Learning System
PII	Personally Identifiable Information
PLATO	Programmed Logic for Automatic Teaching Operations
R&D	Research and Development
RFID	Radio Frequency Identification
ROI	Return on Investment
SaaS	Software as a Service
SAKI	Self-Adaptive Keyboard Instructor
SAMR	Substitution Augmentation Modification Redefinition
SAT	Scholastic Assessment Test
SCORM	Shareable Content Object Reference Model
SIEM	Security Incident and Event Management
SOC	Security Operations Centers
STEM	Science, Technology, Engineering, and Mathematics
TAPAS	Tailored Adaptive Personality Assessment System
TECOM	Training and Education Command (part of the U.S. Marine Corps)
TED	Technology, Entertainment, and Design
UI/UX	User Interface/User Experience
VR	Virtual Reality
xAPI	Experience Application Programming Interface
XML	Extensible Markup Language
xMOOC	Extended Massive Open Online Course

Foundations

CHAPTER 1

MODERNIZING LEARNING

J.J. Walcutt, Ph.D. and Sae Schatz, Ph.D.

The 21st century is marked by significant technological progress in every field. For learning and development, these advancements have helped us realize the promise of "anytime, anywhere" learning as well as learning personalized to individual needs. More than that, emerging capabilities have thrown open the door to transformative possibilities, facilitating learning at scale, optimizing learning in response to large and diverse data sets, and developing fully integrated talent management systems for managing and enhancing the future workforce.

Emerging technologies are not only changing the formal education and training landscape, they're also changing our access to—and relationship with—information and, by extension, affecting the soul of how we think, interact, develop, and work. Our expectations for educational institutions, how and where learning occurs, and what personal developmental looks like have changed—and will continue to evolve into the future. The preK–12 system, higher education, federal and state governments, employers, and military must similarly adapt to accommodate.

The landscape of learning has broadened, now encompassing the full spectrum of formal, informal, and experiential training, education, and development. The traditional concept of education is changing. Employers are placing less value on formal degrees. Instead, experience matters. Life skills, such as grit and teamwork, matter. Performance-based credentials, including competency badges and micro-certificates, are taking the place of transcripts to document individuals' traits, talents, skills, knowledge, preferences, and ex-

perience. Similarly, age is becoming less of a marker of knowledge, skill, and capabilities. These shifts, in turn, are disrupting conventional career trajectories, as age correlates less and less with income and leadership potential, and even changing the way we perceive employment and define our value as contributors to our society.

We use the phrase "**future learning ecosystem**" to describe this new tapestry of learning. At the highest level, the future learning ecosystem reflects a transformation—away from disconnected, episodic experiences and towards a curated continuum of lifelong learning, tailored to individuals, and delivered across diverse locations, media, and periods of time. Improved measures and analyses help optimize this system-of-systems and drive continuous adaptation and optimization across it. Its technological foundation is an "internet for learning" that not only allows ubiquitous access to learning, it also provides pathways for optimizing individual and workforce development at an unprecedented pace.

This book focuses on the human and organizational aspects of the future learning ecosystem. It provides key terms and models, and it helps identify the diverse professional sectors involved in the realization of this vision.

The United States Government has recognized a need for coordination among the communities of learning scientists, organizational psychologists, software and hardware engineers, teachers, talent managers, administrators, and other innovators contributing to this concept. Simply organizing the multiple, interdependent layers of the future learning ecosystem represents an enormous undertaking, more so because its many facets must evolve in concert. Improving school classrooms, for instance, means little unless we also transform how those experiences translate to collegiate, trade, business, and public-sector settings. Similarly, developing systems for earning and communicating credentials creates scant value, unless we also understand how to authentically measure the skills and attributes they accredit. And finally, even if we successfully reshape every aspect of our learning and development systems, we

> The **future learning ecosystem**—a holistic, lifelong, personalized learning paradigm—represents a contrast to the Industrial Age model of time-focused, one-size-fits-all learning

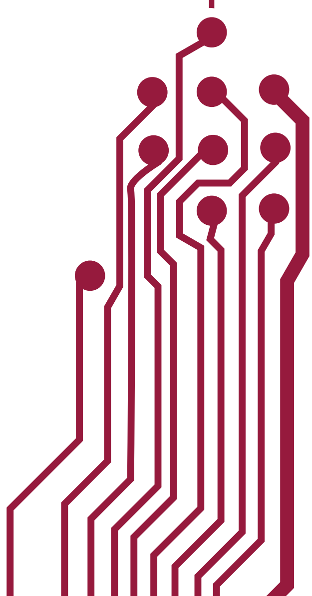
must simultaneously consider the larger cultural and societal shifts affected by this new approach. How will the reconceptualization of learning affect jobs, self-worth, loyalty to businesses, power dynamics, access to education, governmental processes, and our nation overall? When the paradigm of learning (something so fundamental to each of our lives) evolves it will have expansive and exciting, but difficult to fully forecast, effects.

WHAT IS LEARNING?

At its most foundational level, learning is any change in long-term memory that affects downstream thoughts or behaviors. The process of learning starts with awareness of stimuli,[1] cognitive encoding of that information,[2] and its retention in memory. Later, the knowledge must be retrievable (that is, not forgotten) and transferable to novel situations.[3] Throughout our lives, every person learns constantly—all the time, every day. What we each learn, however, its veracity, applicability, intelligibility, and whether it aids or limits performance all vary significantly. Each day, we must reconcile among the complex, competing information vying for our attention—all vying to "teach" us.

Contributions from diverse fields—including **IT**, **data science**, **psychology**, and **learning science**—form a repository of complementary recommendations; together, these define the framework of the future learning ecosystem

These myriad science and technology advancements form the alloy needed to develop optimized learning solutions that **maximize efficiency** while **expanding effectiveness**



The concept of learning applies across performance domains, not only to cognitive development. It necessarily includes physical and emotional aspects as well as inter- and intrapersonal, social, and cultural components. Certainly, learning occurs in formal settings, in grade school classrooms or professional workshops, but it also happens in self-directed, just-in-time, social, experiential, and other informal ways.[4] These varied experiences accumulate in long-term memory and, fused together, affect how we respond to the world.[5] In other words, formal learning in combination with other life experiences collectively determines someone's readiness for work, public service, and other life challenges.

Surfacing the Iceberg

To date, our education and training systems have generally focused on the delivery and documentation of formal learning. As a result, we've fostered a society that values the accreditation of formal training and education (think college degrees) and proxy measures of aptitude (time-based promotions) rather than life experiences and direct measures of competence. Of course, this is based largely on our inability to measure, analyze, and share data about the latter. With advances in technology, however, we're surfacing informal learning.

> In talking about learning, enough with the barriers. We're interested in **outcomes**. I want **effective** learning. I want **measurable** learning. I want learning that results in combat capability. That's what we're looking at, in terms of learning science, from our perspective inside the Pentagon. That's where I'm pushing our folks.
>
> **Fred Drummond,** Deputy Assistant Secretary of Defense for Force Education and Training, U.S. Department of Defense

The growing visibility of, and access to, informal learning is reshaping our conceptualization of learning: Increasingly away from a separate, fenced-off and time-based activity and towards an integrated, diverse lifelong learning continuum where all experiences and development add to an interdependent set of holistic competencies. This paradigm shift means education is no longer viewed as a linear and finite pathway, starting in grade school and culminating with a high school or university degree. Books and teachers, and other hierarchical authorities, are no longer the primary gatekeepers of knowledge. Vocational schools and formal apprenticeships no longer serve as the primary pathways to develop trade skills. Individuals can even cultivate their athletic abilities through self-developed and informal learning channels.

Informal learning means more than just self-directed study. Consider, for instance, when a young person travels overseas for the first time. Perhaps without intention, she learns about other cultures, people, history, and food, as well as other, more subtle lessons about social dynamics, cosmopolitanism, and even self-awareness. Undoubtedly, such experiences are learning, that is, they impact long-term memory and change us. But how might society, teachers, or employers value such learning? How do we record or account for such experiences? How can we define and measure such seemingly intangible qualities, such as worldliness, emotional maturity, or empathy?

21st Century Competencies

Elusive personal characteristics, such as good judgment and social awareness, have always mattered. Increasingly, however, pundits are emphasizing new capabilities that reflect the changing demands of the world. Automation driven by artificial intelligence, ever-increasing computing power, big data, advanced robotics, and the proliferation of low-cost advanced technologies are the shifting nature of work, along with the organizational dynamics of business, government, and society.

Technology is replacing the physical—and intellectual—tasks of many professions, from bus drivers and construction workers to medics and lawyers. Jobs involving manual labor, memorizing procedures, calculating solutions, and even synthesizing diverse information into novel forms are fast becoming the purview of computers. Meanwhile human work increasingly focuses on social and cultural factors, creativity and creative problem solving, digital literacy and technology partnership, and rapid adaptability. Modern core competencies tend to emphasize higher-order, more nuanced and sophisticated capabilities in lieu of fact-based knowledge or procedural skills. Similarly, where in the more recent past, highly skilled professionals typically advanced by focusing on narrow disciplines, today's savants are often "expert generalists" able to synthesize across disciplines, learn new concepts and contexts rapidly, and adapt to changing conditions.

"

There's a foundational set of cognitive, intrapersonal, and interpersonal skills that provide the flexibility, adaptivity, and capability people need to navigate through the kind of constant change, discontinuous, and sometimes irrational situations that pervade the 21st century.

Education should focus on that, much more than it has in recent years, because if we don't make that shift, we'll develop a very brittle set of people at a time when adaptability will be core for their survival.

Christopher Dede, Ed.D.

Timothy E. Wirth Professor in Learning Technologies in the Technology, Innovation, and Education Program, Harvard University

In contrast to prior decades, there's a greater expectation for individuals to learn continuously and develop new capabilities across their entire careers. In large part, this is spurred by the rapidly changing world around us. Pulitzer Prize winning author Thomas Friedman has dubbed this time-frame the "Age of Acceleration," reflecting the exponential growth in technology and unbridled transformation across the globe.[6] To excel in this age, we must learn to thrive in volatility and complexity. We need deep understanding, across a range of cognitive, affective, interpersonal, and physical competences, and

refresh those capabilities as situations evolve. We need to think in terms of system dynamics, applying a strategic understanding of complex systems and the far-reaching effects of actions taken within them. Organizations, too, must learn to shift and grow with evolving needs, rapidly capturing and integrating lessons learned and enabling the disseminate of new ideas painlessly across their enterprises.

In short, to develop and maintain 21st century competencies, individuals require a greater breadth of interdependent knowledge and skills, at an increased depth, that is, more advanced levels of nuanced capabilities, and these competencies must be acquired at a more rapid velocity. To meet such demands, we must embrace continuous learning, find more efficient ways to develop and maintain relevant knowledge and skills, and develop reliable feedback loops that ensure our systems remain relevant in our ever-changing environment. In other words, we must profoundly redesign the integrated continuum of formal and informal training, education, and experience.

FUTURE LEARNING ECOSYSTEM

The future learning ecosystem is a substantive reimagination of learning and development. This concept recognizes the increasing need for cognitive agility, meaning learning is no longer viewed as a single event—nor even a series of events—but rather as a lifelong experience of continual growth. Second, the pathways through which learners progress must be personalized to their unique attributes, skills, interests, and needs in order to achieve necessary effectiveness and efficiency in learning. Finally, instruction and information presentation methods must more strongly emphasize deep learning and expedite the transfer of learning from practice to real-world settings.[7]

Extensive research, across myriad disciplines, has already examined many aspects of the future learning ecosystem. However, to achieve its full implementation and maximal benefits, it's necessary to harmonize the advancements in learning science, technology, data science, organizational dynamics, and public policy.

Technological Infrastructure

Information technology forms the enabling foundation of the future learning ecosystem. Instructional systems, interoperability standards, cross-platform data integration, and centralized software services form the sinews and nerves that transform today's stovepiped, staccato learning episodes into a holistic lifelong experience. Data schemata, technical standards, and governance conventions enable the recording, aggregation, and analysis of diverse learning events—opening the possibility for substantial personalization and data-driven enterprise adaptations. In other words, an integrated, technological-enabled learning architecture unlocks the anticipated transformation in learning. It means that learning can become pervasive—truly accessible anytime, anywhere, in many forms, and for many functions; and accordingly, learning can be tailored for optimal effect.

Design

Where technology will open a new world of learning possibilities, learning science and learning engineering—the thoughtful *design* of learning components and systems—will allow us to capitalize on it. The future learning ecosystem opens the aperture of learning and changes its core characteristics. The classic instructional systems design model no longer suffices. The design of learning, at both the local and enterprise levels, will need new theories and practices. Learning designers will need to understand how to differentially apply diverse technologies, blend disparate delivery modalities into holistic

To realize the future learning ecosystem vision, six critical areas must align.

TECHNOLOGICAL INFRASTRUCTURE

Flexible, interoperable technologies for pervasive learning

DESIGN

Intentional methods applied to optimize learning

COMMITMENT

Contributions to a shared vision across communities

GOVERNANCE

Negotiation of standards, conventions, and ethics

POLICY

Regulations and recommendations for behavior

HUMAN INFRASTRUCTURE

Diversely skilled individuals and organizational structures

experiences, build-in and apply learning analytics, balance practical logistics against learning outcome criteria, incorporate learning and development into personnel and workforce systems, and perform all these actions within a heterogeneous system-of-systems, which they only partially control.

Commitment

The term "ecosystem" refers to complex, interconnected systems. In stark contrast to today's more hierarchical training and education events, where the teacher reigns within his classroom or the trainer dictates the design of her curriculum, achievement of the future learning ecosystem requires collective coordination across diverse communities. The benefits of the future learning ecosystem can only be realized through their gestalt. Learning designers must embed ways to capture learning data, ideally using shared semantic vocabularies. Technology vendors must eschew proprietary, closed systems and embrace open architectures and interoperability standards. Early childhood educators must plan their curricula with postsecondary, workforce, and community intersections in mind. Parents, learners, teachers, administrators, human resource planners, and organizational leaders will need to buy-in to this concept—and actively contribute to its realization. While interoperable technologies may form the foundations of the future learning ecosystem foundations, the social contracts followed by the ecosystem will give it breadth and traction.

Governance

The future learning ecosystem grows from organizational coordination, technological interoperability, and the aggregation of learning data across diverse technological and administrative boundaries. Even without (especially without) a hierarchical leadership structure, such a complex system requires sophisticated governance processes. Cross-sectional governance bodies will

> The crisis across the nation is that there is so much disparity between what each child can access. The system has to be pervasive. The dream of America is that all Americans should have a free education through 12th grade.

Alfred Harms, Jr.

Vice Admiral, U.S. Navy (Ret.); President, Lake Highland Preparatory School; Special Assistant to the President and VP for Strategy, Marketing, Communications and Admissions, University of Central Florida

need to negotiate the conventions for sharing and protecting individuals' data, for designing and updating shared application programing interfaces, and for balancing the competing interests of educational, commercial, and governmental organizations. Accreditation bodies will need to evolve to accommodate new types of assessments and credentials. These governance bodies will also have a responsibility to consider the social and societal impacts of this new learning system. They will need to navigate a spate of new social and ethical considerations, envision new legal and regulatory rules, and attempt to envision the emergent risks and opportunities as the system matures. While government will undoubtedly play a role, we—the stakeholders across highly

diverse communities—have a responsibility to actively participate in these governance processes. Unlike a walled garden, where appointed caretakers can curate the design, the future learning ecosystem requires the community to take an active role in steering its ecology.

Policy

Governance bodies, along with the actual government and key performers within the ecosystem, will inform policies for the future learning ecosystem. Policy is the blueprint of recommendations and regulations that define guidelines for behavior within the system. Recommendations might include best practices for collecting and personalizing learning in response to data. Regulations, or rules put in place to protect the public, might include guidance on the privacy, ownership, and commercialization of learners' data. Nearly all innovation carries a double-edged sword: Creative foresight, social accountability, and ethical principles will need to guide employment of the future learning ecosystem for our public sector as well as personal and business-related interests.

Human Infrastructure

Although technological advances make the future learning ecosystem possible, its implementation requires a multitude of differently skilled (human) contributors. Hence, as we develop its technology infrastructure, learning theories, and organization processes, we must also cultivate the future learning ecosystem's critical human infrastructure. A new subdomain of technologies and learning-focused data scientists are clearly needed. The system will also require numerous insightful talent managers, learning engineers, and courseware designers. Teachers, trainers, coaches, and mentors will need to be empowered and trained to take full advantage of this new milieu of learning. Even individual learners will play a key role—not only in the "consumption"

It's about the **dignity** of work. How do we create in our country a sense of work **pride**? We have an obligation and opportunity to create an environment where everyone has **skin in the game**.

U.S. Congressman Jack Bergman

Lieutenant General, U.S. Marine Corps (Ret.);
…from a presentation at the 2018 I/ITSEC Conference

of learning but also in crowdsourced, peer-to-peer, and collaborative learning. The future learning ecosystem will affect us all, and in turn, we can each shape and contribute to it.

Blueprint for Implementation

This book examines the future learning ecosystem concept, our collective progress towards its realization, and the pivot our systems and society need to make away from formal, detached education and training towards experiential, personalized, interconnected learning journeys. The U.S. Government's ADL Initiative has taken the lead in designing this book and is helping to coordinate across the broad stakeholder community, both conceptually and practically. The following chapters in this publication provide a snapshot of the achievements the ADL Initiative and other contributors have made to date, what we need to build for tomorrow, and what this near-future system will enable our children, workforce, society, and military personnel to achieve.

Learning is a journey, not a destination.

CHAPTER 2

HISTORY OF DISTRIBUTED LEARNING

Art Graesser, Ph.D., Xiangen Hu, Ph.D.,
and Steve Ritter, Ph.D.

Learning science and associated technologies have advanced dramatically, and disruptively, over the last 30 years, and they will no doubt continue to evolve through the foreseeable future. To proceed with wisdom, it's prudent to review the past and to examine how we came to our current state, what achievements and pitfalls we encountered, and what lessons might translate into the future learning ecosystem.

This chapter specifically examines the evolution of distributed learning. Under this moniker, we've included related terms, often used synonymously, such as distance learning, distributed or distance education, web-based and web-enabled instruction, online learning, and e-learning—just to name a few! More recently, "distributed learning" has come to reference an even-wider perspective, sometimes incorporating concepts such as distributed simulation, mobile learning, augmented and virtual reality, computer-assisted instruction, and web-based self-directed learning. We touch on those, too. Even certain generic terms, such as technology-enhanced learning or educational technology, are sometimes used to reference distributed learning, and where applicable, we've included those concepts as well.

Although we recognize distinctions among these terms, this isn't an academic chapter on the nuances of vocabulary. Instead, we attempt to take readers on a brief journey, starting with the foundations of distributed learning and

considering its evolutionary progress, across many different fields, towards a unified, technology-enabled interconnected learning paradigm.

Certainly, others have written more robust historical accounts, for those interested in more detail. For instance, in a now classic article, Soren Niper outlines the three historic generations of distance education, starting with correspondence teaching, followed by multimedia offerings (e.g., cassettes and television broadcasts), and finally the third-generation, involving information and communication technologies.[1] Building upon Niper's framework, Mary Simpson and Bill Anderson wrote a brief and accessible overview of the "History and Heritage in Distance Education."[2]

For truly comprehensive treatments, refer to Michael Grahame Moore and William Anderson's *Handbook of Distance Education* originally published in 2003 (or Moore's update of that classic in 2013).[3] Also review Paul Saettler's thorough examination on *The Evolution of American Educational Technology*[4] and J. Michael Spector and colleagues' *Handbook of Research on Educational Communications and Technology*.[5] In the latter, Michael Molenda's "Historical Foundations" chapter offers a particularly readable treatment of the field's development.

1980s

In all historical accounts of distributed learning, authors seem compelled to highlight its analog foundations—hand-painted slides illuminated by oil lamps in the 17th century, correspondence learning by mail in the 18th century, or silent films in the early 20th.[6] However, for our purposes, the history of distributed learning meaningfully begins in the 1980s. This decade witnessed the rise of personal computers, with widespread adoption in most schools beginning around 1983.[7] Their proliferation ushered in Niper's so-called

third-generation of distance education, shifting away from "boxes of books" and towards computer-based learning experiences.

Computer-based learning generically refers to the use of computers to access training and education. It can involve synchronous and/or asynchronous activities, delivered via networked or standalone stations. Early experiments in computer-based learning began in the late 1950s and early 1960s, with the University of Illinois's PLATO project often cited as the first computer-based system and Gordon Pask and Robin McKinnon-Wood's SAKI as the first adaptive trainer. SAKI, which stood for Self-Adaptive Keyboard Instructor, used a mechanical device to modify typing exercises in response to learners' performance, typically shortening training time by one-half to two-thirds as compared to conventional instructional methods.[8]

Student using PLATO III, 1970; courtesy of the University of Illinois at Urbana-Champaign Archives

These experiments gave rise to the first-generation of computer adaptive tutors, often called "computer-assisted instruction tutors." In his meta-analytic review of computer-assisted instruction from this time-frame, James Kulik found students typically performed better (with an average effect size of .35 standard deviations), completed learning activities more efficiently (about a quarter to a third more quickly), and tended to have more positive outlooks on learning with computer-assisted instruction.[9] Groundbreaking systems emerged around this time-frame, including intelligent tutoring systems, which were a substantial advance over computer-assisted instruction tutors with their very simple assessment, feedback, and lesson-branching rules. Landmark early intelligent tutors included Alan Lesgold's SHERLOCK, John Anderson and colleagues' LISP tutor, and John Seely Brown and Richard Burton's SOPHIE.[10] These systems used automated computational procedures to guide

learners through problem steps, give hints, and provide teacher-like feedback. The more advanced intelligent tutoring systems showed even higher learning gains, an effect size of .76 standard deviations, according to more recent meta-analyses conducted by James Kulik, Phil Dodds, and Dexter Fletcher.[11]

Many of the early instructional technologies weren't yet *distributed*, but that was changing. Throughout the 1980s, U.S. federal agencies, including the Department of Defense, National Science Foundation, and Department of Education sponsored significant research on computer-based instruction, including distributed learning.[12] In 1989, the U.S. Office of Technology Assessment delivered a Congressional report, called *Linking for Learning*, summarizing the progress such investments had made over the decade:

> Distance learning is expanding. …a national survey of representative school districts indicated that an estimated 22 percent of school districts now use distance learning, some 33 percent expect to be using these resources by 1990. The second trend is more subtle. Distance learning is changing educational boundaries—boundaries traditionally defined by location and by institution. In the pooling of students and teachers, distance learning efforts reconfigure the 'classroom.' No longer bound by the physical space, classrooms extend to other students in the same district, to other districts, to other States, or even across national borders.[13]

The report also called for increased research on distributed learning, particularly regarding its effectiveness, methodology, and design. "The quality and effectiveness of distance learning are determined," it explained, "by instructional design and technique, the selection of appropriate technologies, and the quality of interaction afforded to learners." This was a job for instructional designers.

The origins of Instructional Systems Design (ISD) trace back to the 1960s, but the 1980s saw a proliferation of ISD models appear in the literature. Roughly around this time, the ADDIE concept also materialized, apparently spontaneously,[14] as a generic framework underpinning the various mod-

els. Traditional ISD approaches grew out of the behaviorist paradigm, and similarly, most early computer-based learning used drill-and-practice tactics grounded in behaviorism.[15] As Kulik observed at the time, “Most programs of computer tutoring derive their basic form from Skinner’s work in programmed instruction. Skinner’s model emphasized (a) division of instructional materials into a sequence of small steps, or instructional frames; (b) learner responses at each step; and (c) immediate feedback after each response.”[16]

ADDIE

Analyze, Design, Develop, Implement, and Evaluate

…an evergreen model, general enough to suit pretty much any process

Some educators in this decade also advanced an industrialized model for distributed learning, as best expressed by Otto Peters. He positively compared distance education to industrial production, citing the division of labor, mass production, realization of economies of scale, and reduced unit costs. His model wasn’t intended as an instructional theory, but rather as an organizational concept that, in his own words, described the industrial “objectification of the teaching process.”[17]

Nonetheless, the state of learning science in educational technology was progressing. The 1980s saw a growing influence from the cognitivist school, for instance, with the development of concepts such as cognitive-load theory. Although this theory’s antecedents began in the 1950s, it wasn’t until the 1980s that John Sweller connected those earlier cognitive principles to practical educational tactics. Based on observations of students studying, Sweller proposed that inherent bottlenecks in our cognitive processes create barriers to learning that teachers can mitigate through careful instructional design. In other words, Sweller’s theory posits that certain factors can increase our cognitive load and distract us from learning the relevant information; more importantly, his theory offered actionable recommendations to teachers and designers for mitigating those distractions, including implications for educational technology designers.[18]

Benjamin Bloom was also exploring the impacts of cognitive science on education. His influential research on the "two-sigma problem" attracted the attention of many learning researchers. Bloom found that students who receive instruction via one-on-one (human) tutoring using mastery learning techniques outperform those who receive group-based instruction in classrooms.[19] This foundational study has become a rallying point for proponents of computer-based adaptive learning.

Although Bloom's classic study, as well as most of the computer-based learning so far, emphasized individual instruction, by the mid-1980s learning scientists had begun exploring more constructivist and collaborative techniques, building upon the constructivist educational theories of Jean Piaget, for example, and of collaborative constructivist Lev Vigotsky.[20] The most radical constructivist educational theories begin with the premise that objective "reality" is unknowable, and, instead, individuals construct a subjective, contextualized reality within their own minds. Less radical constructivists still emphasize the active construction of knowledge that tends to settle into the constraints of the objective physical and social world. For educational environments, this implies that students learn best by engaging with instructional material, actively generating learning experiences rather than passively interpreting information. Constructivism catalyzed a change in educational theory, moving it away from instructor- and content-centric views and towards a learner-centric one.[21] Social constructivism takes this premise a step further, emphasizing collaboration and the impacts of social interactions on learning and the construction of knowledge by groups.[22]

Social constructivist educational theories spurred the development of computer-supported collaborative learning, software designed to support interactive learning and computer-mediated communications. Businesses and universities began to develop communicative and educational technologies, such as Xerox's NoteCards and Carnegie-Mellon University's Andrew.[23] Marlene Scardamalia and her colleagues from the University of Toronto also made

significant impacts on this field. For instance, they experimented with computer-supported intentional learning environments that enabled collaborative meaning-making by helping students share ideas, pictures, and notes via network computers.[24] Projects like this influenced the wider field of educational technology, encouraging a fundamental shift towards social learning.

Such interest helped foster the idea of a "virtual classroom," a multi-person anytime, anywhere learning environment facilitated by networked computer-mediated communications. "Suddenly it came to me," Starr Roxanne Hiltz, from the New Jersey Institute of Technology, explained. "A teaching and learning environment did not have to be built of bricks and boards. It could be constructed in software. It could be Virtual! In an era when many teachers and students have their own microcomputers, it was no longer necessary for them to travel to a classroom…the classroom could come to them, over their telephone lines and through their computer."[25]

The digital collaborations spawned in the 1980s led to contextually rich environments in the ensuing decades. While Hiltz and her colleagues developed virtual classrooms, other built entire *worlds*. Virtual worlds, or "synchronous, persistent network[s] of people, represented as avatars, facilitated by networked computers"[26] and synthetic environments, or realistic simulated environments, similarly emerged during this era. One example of this is Michael Naimark's concept of "surrogate travel," virtual recreations of real environments navigable via a LaserDisc.[27] Another instance is the NASA Ames Laboratory's virtual reality system, which used stereoscopic head-mounted displays and a fiber-optic data glove. Finally, *Habitat*, developed by Lucasfilm Games in association with Quantum Computer Services, Inc., is often-cited as one of the first attempts to develop a large-scale, multiplayer, commercial virtual world.[28] Such systems would require several intervening decades to reach fruition, but the contributions of these forerunners can't be understated.

While the education community developed virtual worlds and collaborative virtual classrooms, the training industry similarly explored collective-learn-

By the end of this the 1980s, "virtual" exploration was demonstrated routinely at NASA Ames and elsewhere. The picture above, taken in 1990, shows an operator using NASA's Virtual Interface Environment Workstation, developed by NASA and VPL Research, Inc.; photo courtesy of NASA.

ing capabilities, in their case, for multi-person training simulations. Promoted by organizations such as NASA and the U.S. military, computer-supported trainers first emerged in the 1940s. Initially, these instructional simulations were used as substitutions for live training that was too costly, unsafe, or otherwise inconvenient. However, during the 1970s, the training community began to value instructional simulation beyond mere substitution, seeing it as a unique instructional tool and a potential platform for team-based practice. Encouraged in part by the demand for collective and improved training, researchers started developing collective, distributed simulation-based training technology. The Defense Advanced Research Projects Agency's (DARPA) Simulation Network (SIMNET), fielded in 1987, serves as a notable example.[29] However, distributed simulation wouldn't become a truly viable learning modality until the 1990s and the rise of the global internet.

1990s

Computer-based learning continued to expand throughout the 1990s, in conjunction with the increasing prevalence of personal computers, improvements in their multimedia capabilities, and advances in computer networking. Most notably, the 1990s were profoundly marked by the growth of the world wide web (invented in 1989), and with it, broad access to networked communications.

The first operational web-based courses appeared in the mid-1990s, and by the end of the decade, around 60% of all U.S.-based universities had web-based offerings.[30] Simultaneously, the e-learning industry emerged. Throughout the '90s, vendors developed tools to help teachers and institutions manage their e-learning resources. The associated software was released under a diversity of titles, including course management systems, virtual learning environments, learning platforms, and managed learning environments, as well as learning management systems and learning content management systems, which remain popular today.

In addition to traditional e-learning, some researchers began to promote adaptive hypermedia. In contrast to typical websites, which provide the same text, links, and multimedia to all viewers, adaptive hypermedia systems create user models of each visitor and then adapt the information and links presented. Peter Brusilovsky and colleagues developed and tested adaptive hypermedia systems that integrated web communication and intelligent tutoring concepts.[31]

Along with adaptive hypermedia, the so-called "second-generation" of adaptive tutors—formally called intelligent tutoring systems—also matured. As one notable example, the cognitive tutors developed by Ken Koedinger and his colleagues trained middle school students in mathematics at thousands of schools throughout the United States and showed impressive learning gains in rigorous evaluations.[32] In their meta-analysis on the topic, Kulik and Fletcher show that intelligent tutors in the '90s reportedly average effect sizes of nearly one standard deviation—gains nearly twice as high as the first-generation of computer-assisted instruction tutors.[33] The learning gains of these intelligent tutors are approximately equivalent to human tutors.[34]

Affective computing originated as a branch of computer science around the middle of this decade, notably by Rosalind Picard.[35] Those researchers examined how to simulate emotions in AI, and they developed ways for machines detect emotions in humans. Both goals would prove relevant for education. The former helped inform research on pedagogical agents, or animated char-

More on page 51

acters that serve as tutors or peers in instructional technologies.[36] The latter would help inform the adaptive responses of personalized learning systems, such as by responding to students exhibiting boredom or frustration.[37] Later, as this discipline matured through the 21st century, researchers such as Rafael Calvo and Sidney D'Mello would develop ways to more reliably, less invasively sense these states, using tools such as eye-trackers, facial and gesture recognition, mouse movements, and posture sensors.[38]

With all of these emerging technologies, it was becoming increasingly clear that new evidence-based principles of learning were needed. One such advancement came from Richard Mayer and his multimedia learning theory. Building on Sweller's cognitive-load theory as well as other cognitive principles, Mayer carefully described learners' mental processes when interacting with multimedia instruction and then offered guidance on optimizing it, such as: Present an explanation in words and pictures rather than solely in words, and present corresponding words and pictures contiguously rather than separately.[39] Mayer's work had significant impacts on the field; it made cognitive science more accessible to educators and gave instructional designers clear advice they could implement.

Instructional theories related to computer-mediated communication also gained traction.[40] Although these concepts emerged in the 1980s, it wasn't until this decade, with its ready access to web-based communication, that they blossomed. Randy Garrison, a prolific scholar in this area, wrote of the time "…we are entering a postindustrial era of distance education characterized by the ability to personalize and share control of the educational transaction through frequent two-way communication in the context of a community of learners."[41] Where the previous decade tended to emphasize the industrial value of distributed learning tools, in the 1990s, theorists such as Garrison began to place greater emphasis on the facilitation of teaching and learning at a distance. Even Otto Peters, who first proposed the industrial model of distance education, asked in the 1990s whether there were "early signs of a 'new

era' which might be called 'postindustrial'?"[42]

While instructional theorists cheered the pedagogical opportunities offered by the world wide web, some universities had even grander designs. In his book, *Mega-universities and Knowledge Media*, John Daniel examined the transformative power of large-scale, open distance learning in postsecondary education, highlighting its promise to decrease costs, create flexibility, and provide greater access to higher education (particularly in underprivileged areas). Daniel specifically examined the solutions offered by mega-universities, such as the British Open University. By definition, these institutions remove barriers to enrollment and serve a minimum of 100,000 students. "Providing education and training for the burgeoning population of the developing world is not only a challenge for the countries concerned," Daniel wrote. "The security of humankind may well depend on it."[43]

The power of the web to change society via education could not be ignored. Marking its impact, the U.S. Congress established the Bipartisan Web-based Education Commission in 1998, part of the reauthorization of the Higher Education Act. In the Commission's subsequent—and evidence-rich—capstone report, titled *The Power of the Internet for Learning*, it urged Congress to make e-learning a center-piece of the nation's education policy, saying "The Internet is perhaps the most transformative technology in history, reshaping business, media, entertainment, and society in astonishing ways. But for all its power, it is just now being tapped to transform education. …It is now time to move from promise to practice."[44]

The six promising trends cited by the Commission's report included greater broadband access; pervasive computing, "in which computing, connectivity and communications technologies connect small, multipurpose devices, linking them by wireless technologies;"[45] digital convergence, or the merging of telecommunications, radio, television and other interactive devices into a ubiquitous infrastructure; education technology standards; emerging adaptive technologies that combine speech and gesture recognition, text-to-speech,

Virtual Fixtures, considered the first immersive augmented reality system, was built by Louis Rosenberg while at the U.S. Air Force Research Laboratory. Pictured above, Rosenberg using the system in 1992; photo courtesy of AR Trends.

language translation, and sensory immersion; and finally, the dramatically decreasing cost of internet bandwidth.

With the benefit of hindsight, we can append several additional trends to this list. One example is mixed reality, a continuum including virtual reality (VR) and augment reality (AR). Although pioneered throughout the 1950s through 1980s, their first practical applications for education and training came in the mid-1990s. VR offerings at that time typically used either head-mounted displays or cave-like projections rooms to create immersive experiences.[46] In contrast to VR, which attempt to wholly replace reality with virtual sights and sounds, AR systems inject virtual stimuli into actual situations, such as overlaying graphics onto a real-time, real-world video. However, in both cases, the technology was still expensive and generally cumbersome—but it has been advancing rapidly. Still, empirical evaluation of the effectiveness of these technologies for improving learning or motivation remains surprisingly minimal, even to this day.

Distributed simulation also saw marked progress during this decade. The developments of SIMNET, the decade prior, had given birth to the era of networked real-time simulations. Now, those same proponents that drove the creation of SIMNET sought to develop synthetic environments capable of seamlessly integrating live, virtual, and constructive simulations within a common environment.[47] Towards that end, engineers were developing new interoperability standards to support synchronous instructional scenarios, including the Distributed Interactive Simulation (DIS) and the High-Level Ar-

chitecture (HLA) protocols,[48] and researchers were examining the viability of using the world wide web for distributed simulation.[49]

The U.S. Government was also looking at better ways to leverage web-based learning, particularly for military and workforce development. These requirements led to the creation of the Advanced Distributed Learning (ADL) Initiative. The ADL Initiative traces its antecedents to the early 1990s, when Congress authorized the National Guard to build prototype electronic classrooms and learning networks for their personnel. By the mid-1990s, DoD realized the need for a more coordinated approach, and the *1996 Quadrennial Defense Review* formalized this by directing development of a Department-wide strategy for modernizing technology-based education and training. This strategy became the original ADL Initiative. In 1998, the Deputy Secretary of Defense directed the Undersecretary of Defense for Personnel and Readiness, in collaboration with the Services, Joint Staff, Undersecretary for Acquisition and Technology and the Comptroller, to lead the burgeoning program. He also directed the creation of a department-wide policy for distributed learning, development of a corresponding "master plan" to carry out the policy, and resources for the associated implementation. Shortly thereafter, aspects of the ADL Initiative grew into a federal-wide program, with a mandate to help unify e-learning systems through coordination, shared technology standards, and the application of modern learning theory.

> The advanced distributed learning strategy requires re-engineering the learning paradigm from a "classroom-centric" model to an increasingly "learner-centric" model, and re-engineering the learning business process from a "factory model" (involving mainly large education and training institutions) to a more network-centric "information-age model" which incorporates anytime-anywhere learning.[50]

Part of the ADL Initiative's mission involves technology standards for distributed learning. In the 1990s, standards such as Hypertext Transfer Protocol (HTTP) and Hypertext Markup Language (HTML) were just appearing. Sim-

ilarly, Extensible Markup Language (XML) was released in the mid-1990s, helping to turn the web from a presentation medium to a data-rich platform and, notably, opening the door to the semantic web.

Whole books could (and most certainly have been) written about the technological advancements seen in the last decade of the 20th century. For our purposes, a few other notable ones included the growing prominence of AI and data mining, availability of natural language interfaces, commercialization of personal digital assistants and associated cellular communications, and creation of DVDs. Unprecedented demand for computational models also developed, encouraging researchers to craft extensive model sets for all manners of industries including airport facilities, call centers, businesses, health centers, and even fast-food restaurants.[51] Cognitive modeling approaches, initially explored in earlier decades, started to be realized in applied systems. DARPA's Pilot's Associate, for instance, incorporated artificial intelligence and cognitive modeling to infer an aircraft pilot's intentions and support her decision making. These sorts of cognitive and neuroscience advances also marked this era, and later lead president George H. W. Bush to designate it "the Decade of the Brain."

2000s

The 2000s continued to see acceleration in learning technologies, aided by expanding broadband access, consumer smartphones, streaming video services, e-book readers, and the rise of social media. As mobile phones permeated across the globe, practitioners embraced mobile learning (or m-learning). In developing nations, m-learning became a lifeline, delivering education to millions of otherwise disconnected or underserved people.[52] Even in industrialized countries, m-learning opened new doors, offering an innovative platform for context-aware, pervasive learning.[53]

Content designed for m-learning often took the form of bite-sized, microlearning chunks. Although microlearning and mobile learning are distinct concepts, the two overlap and intersect considerably, with both emphasizing flexible self-pace content, and contextualization of learning. Smartphone-based microlearning helped realize the original promise of anytime, anywhere—truly ubiquitous learning, delivered at the point of need.

While m-learning developed, conventional online learning continued to grow. By the end of the decade, 80% of U.S. school districts offered online courses.[54] Nearly all universities included some form of e-learning, and many corporations, such as Cisco and AT&T, had migrated substantial portions of their corporate training online.[55] Commercial learning management systems, such as Blackboard and WebCT, held prevalent market share, and open-source competitors, such as Moodle and Sakai, were gaining popularity.

The growing demand for e-learning software reinforced the need for associated technology standards, such as the Learning Object Metadata (LOM) and Dublin Core for defining content metadata, and the Sharable Content Object Reference Model (more commonly known as SCORM) specifications for making e-learning content interoperable across systems.[56] Dovetailing with these specifications, researchers promoted the concept of "instructional objects," or encapsulated learning materials that could be remixed and reused. As Fletcher predicted in 2005:

> …the emphasis in preparing materials for technology-based instruction (or performance aiding) will shift from the current concern with developing instructional objects themselves to one of integrating already available objects into meaningful, relevant, and effective interactions.[57]

With such goals in mind, proponents began creating learning registries and content repositories—federated systems intended to support seamless discovery and access to content, such as the Content Object Repository Discovery and Registration/Resolution. Architecture (CORDRA)[58] and the Multimedia Education Resource for Learning and Online Teaching (MERLOT) project.

Although the idea of object registries has floundered somewhat in the intervening years,[59] the promise of ready access to learning continues to gain ground.

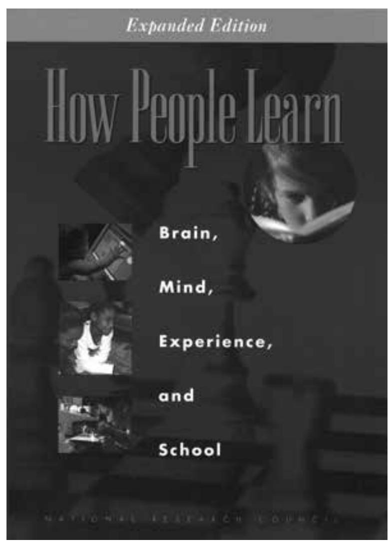
Interest in making education broadly accessible spurred the open educational resources movement, committed to making learning resources free and widely available to teachers, trainers, and learners.[60] Creative Commons, and its open licensing model, formed around this time, and Wikipedia launched in the same year. Wired magazine also coined the term "crowdsourcing" in the mid-2000s, defining it as "…taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call"—a concept the open educational community quickly embraced.[61]

The campaign for open education also drove development of massively open online courses or MOOCs. Although MOOCs wouldn't become widely popular until 2012, they first appeared in 2008. Platforms, such as Udemy and Peer 2 Peer University, were founded soon after, offering free online courses to thousands of students. MOOCs also introduced a new learning paradigm. The first MOOCs grew out of connectivist learning theory, developed by George Siemens and Stephen Downes. Dubbed "a learning theory for the digital age,"[62] connectivism suggests that knowledge is distributed across networks of connections—particularly in our complex modern world. Consequently, it emphasizes continuously learning, the ability to see connections among information sources and across different fields, and the importance of current, diverse knowledge. The original, connectivist MOOCs are sometimes called cMOOCs, to accentuate their emphasis on social learning, cooperation, and the use of collaborative learning tools.

In addition to connectivism, several other learning theories developed throughout the 2000s. For example, the National Research Council published *How People Learn*,[63] an influential book encapsulating far-reaching insights on classroom teaching and learning. Lorin Anderson and David Krathwohl

released their two-dimensional revision of Bloom's famous taxonomy.[64] David Merrill published his *First Principles of Instruction*,[65] which helped to integrate competing behaviorist, cognitivist, and constructivist learning theories. Steve Fiore and Eduardo Salas published a compendium dedicated to applying collaboration dimensions of learning science to online learning,[66] and the Institute of Educational Sciences released its seven cognitive principles of learning, backed by solid empirical data and readily applicable in the classroom.[67]

The research and practice of personalized learning environments matured, growing out of the fields of constructivism and adaptive hypermedia[68] as well as intelligent tutoring systems and artificial intelligence in education.[69] The flipped classroom concept, originally developed in the 1990s,[70] gained widespread popularity. This instructional technique reverses the classic schoolhouse model by delivering didactic instructional content outside of the classroom and using face-to-face time for interactive learning, notably those activities traditionally reserved for homework. The growth of online learning tools and streaming technologies made flipped classrooms more accessible to teachers. Salman Khan, who founded the Khan Academy in 2004, also significantly contributed to their popularity, helping to broadly familiarize teachers and the public to the concept.[71]



The influential *How People Learn*, and its sequel *How People Learn II*, are openly available from the National Academies at www.nap.edu

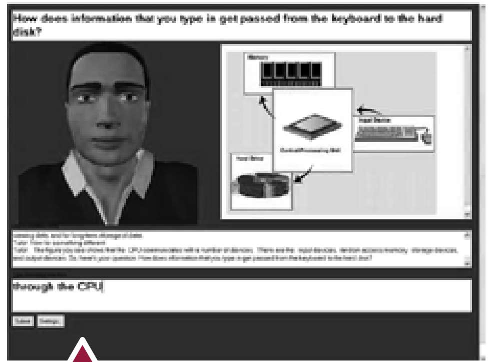
Likewise, the application of spaced learning tactics gained widespread acceptance during this decade (one of the seven cognitive principles of learning by the Institute of Educational Sciences[72]), although its roots date back to the 19th century. Also called

distributed practice, this principle highlights that learning occurs best (that is, is best encoded in and made retrievable from long-term memory) when its presentation happens over time rather than massed into shorter, less frequent intervals. Paul Kelley, headteacher at a British high school, helped popularize spaced learning in his 2008 book *Making Minds*, which drew notably from neuroscience principles. In it, he wrote, "As of this moment, scientific analysis of learning has hardly made any impact on education. In contrast, knowledge in areas of technology and science generally is growing rapidly. As we will see, this knowledge is often quite at odds with the conventional wisdom of education. The scientific understanding of the human brain, and how it works, is beginning to show that learning is not an abstract transmission of knowledge to an infinitely plastic intelligence but a biochemical process with physical limitations."[73]

Conversation-based learning environments with pedagogical agents and avatars on the web flourished during this decade—into and the future. Students could learn by holding conversations in natural language, such as in the *AutoTutor* system developed by Art Graesser and colleagues[74] and in virtual reality environments, such as Crystal Islands developed by James Lester and colleagues[75] and the Tactical Language and Culture System developed by Lewis Johnson.[76] These systems promoted constructivism and collaboration, with engaging social and emotion sensitive interaction.

Desire for increased, evidence-based rigor was also seen among assessments of learning.[77] Although not a new concept, learning scientists strongly promoted the use of tests for learning,[78] and urged teachers to move away from multiple-choice items in favor of more active techniques, such as writing essays, which most teachers didn't know could also be automatically graded with high reliability.[79] Relatedly, by the end of this decade, increasing computing power and the expanding amounts of learning data encouraged the development of learning analytics, led by George Siemens and his colleagues,[80] and educational data mining, led by Ryan Baker and his colleagues.[81] These

closely related fields, each evolved to have professional societies and journals of their own, apply principles of data science to learning data, often collected from interaction logs or assessments built into educational technologies. Although researchers continue to debate the finer points of these definitions, both fields emphasize the use of measurement, collection, and analysis of data relevant to learning and development, along with the application of those analyses for enhancing some aspects of the learning system.[82]



An early AutoTutor interface from the 1990s, courtesy of Graesser et al.

2010–PRESENT

From a learning science and technology lens, the 2010s blend into the prior decade, but there are technological advances that have changed the landscape dramatically. This decade ushered into our world accurate spoken language understanding, smartphones at all spectrums of societies, ubiquitous gaming and social media, tracking of performance in log files at fine grain sizes, sensing algorithms that detect emotions and identity of people, MOOCs on thousands of topics, hyper-realistic animated agents, collaborative problem solving, and disruptive AI that will replace many jobs. It is impossible to forecast the most impactful inventions of our current era. However, a few trends already stand out for our current decade, but whether they will stand the test of time remains to be seen.

MOOCs have continued to develop, although not without their critics and concerns. More commonly, today, MOOCs follow the so-called Extended MOOC model. These xMOOCs share some features with cMOOC, including open

“We just finished up a manuscript for the *Journal of Cognition and Development** describing where we’ve come from in the learning sciences and where we’re going. We traced the funding investments from the 1970s until now and noted that the funding is coming from different places, including multiple federal agencies and private foundations. For example, the Office of Naval Research has a long track record of funding in this space, as does the Department of Education in many capacities—not just through the Institute of Education Sciences but also through predecessors, like the National Institute of Education.

Federal agencies take different approaches to funding this research, in part due to the differences in agencies’ missions, but the goal of understanding how people learn is shared. We observed that these investments either took a content-agnostic approach—studying learning principles typically studied in the laboratory that may have wide ranging benefits for learning, such as retrieval practice for example—or, they took a content-dependent approach. For instance, investments in reading were a focus in the ‘70s and ‘80s and then again in 2010 with the Institute of Education Sciences’ *Reading for Understanding Initiative*… This content-dependent approach is a very different approach than the content-agnostic one; it’s about identifying nuances and challenges within a content area from a cognitive science angle.

Both the content-agnostic and content-dependent approaches have been funded in parallel over the years, and both have made important contributions to our understanding of how people learn. You need the content agnostic approach to identify promising learning principles but the content dependent is also necessary because each content area has unique needs. Ultimately, we need to combine these two approaches; however, they’re taken by different types of cognitive scientists. It would be beneficial if those groups started working together.

Erin Higgins, Ph.D.
Program officer within the Institute of Education Sciences, U.S. Department of Education

*Look for Higgins, Dettmer, and Albro, currently in press

access and large scale. However, where cMOOCs stress connectivist learning, xMOOCs generally use more traditional, instructivist methods, focusing instead on scalability. Spanning both industry and academia, the most popular xMOOCs launched in 2012 including Coursera, edX, and Udacity. These platforms, which attempt to provide learning at scale, have been significantly aided by the development of cloud computing in the 2000s and by the consumer release of Amazon Web Services and Microsoft Azure. Cloud systems made the "service" model of computing viable, freeing software applications to become device and location independent, allowing for more frequent application updates, and creating a near-infinite capacity to scale on-demand.

Cloud computing also helped realize the Internet of Things (IoT), the network of smart devices that can connect to networks and share data. Cisco's Chief Futurist, Dave Evans, estimates the IoT was "born" around 2008 or 2009, but researchers have only begun exploring its applications for learning.[83] In the context of education and training, IoT helps bridge real and virtual contexts, allowing learners to interact with networked physical objects that also have digital footprints.[84] These objects might include embedded RFID sensors, spatial beacons, or wearable technologies, such as FitBits or Google Glass.[85]

Some wearable technologies also incorporate neurophysiological sensors, such as heart-rate monitors or eye-trackers. The commercial versions of these still usually suffer from noisy data, and are only starting to be meaningfully integrated into applied learning systems. Applications of psychophysiological tools (e.g., eye-tracking, skin conductance), brain imaging tools (e.g., fMRI, EEG), and affective computing are rapidly advancing in laboratory contexts, and researchers are already having success detecting students' emotions from low-cost video feeds, pulled from the stock cameras on phones and laptops.[86] Further, several new DARPA programs are teasing science fiction–like results as they explore neural interfaces; these have already shown to enhance human cognition and learning in clinical experiments, and they could one day enable complex human-machine teaming.[87]

Each of these applications produces an overwhelming amount of digital by-products—a smog of data. The explosion of learning data, and corresponding growth and diversity of learning platforms, has once again created a need for new technology standards. The ADL Initiative began developing the Experience API (xAPI) in 2011, with its first public release in 2013. xAPI lets software applications share (potentially big) data about human performance, along with associated instructional or performance context information. xAPI helps analysts aggregate and collectively analyze learner data from different systems—from traditional LMSs to mobile devices, simulations, wearables, and physical beacons. xAPI also represents one piece of the developing Total Learning Architecture, a set of specifications that promises to connect the many dissimilar and stovepiped learning technologies into a more cohesive system-of-systems.

The sophistication of the 21st century learning environments and complexity of data within them have the unfortunate consequence of driving up costs. An expensive system, say costing $50 million, is economically plausible if it delivers training to 10 million learners—but not if only 100 people benefit. There have been a number of efforts to reduce costs in addition to improving learning and motivation. For example, intelligent tutoring systems have been expensive to develop in the past, so the Army Research Laboratory, led by Bob Sottilare, organized a community of over 200 researchers and developers to articulate adaptive instructional system guidelines in a 7-volume book series that covers learner modeling, instructional management, authoring tools, domain models, assessment, team tutoring, and self-improving systems.[88] This Generalized Intelligent Framework for Tutoring (GIFT) initiative also includes a functional computational architecture that can be used to develop and test systems.

Another emerging approach to reducing costs is to use crowdsourcing in content creation and modification, with machine learning to automatically tune quantitative parameters in self-improving systems.[89] Unfortunately, the field

T3 INNOVATION NETWORK

In early 2018, the U.S. Chamber of Commerce and Lumina Foundations launched the T3 Innovation Network to bring businesses, postsecondary institutions, technical standards organizations, human resource professionals, and technology vendors together to explore Web 3.0 technologies for an increasingly open and decentralized public–private data ecosystem. Since its kickoff, the Network has grown into a thriving network of over 128 organizations who are addressing three key challenges: (1) The need for harmonization among technical data standards groups to ensure data is interoperable and shareable across systems and stakeholders; (2) The need to apply AI solutions to improve how learning objectives, competencies, and skills are authored, translated, and distributed; and (3) The need to empower learners and the American worker with data to improve their agency and ability to manage and connect to opportunities in the talent marketplace.

still lacks a systematic, widely accepted approach to estimating costs and development time for building and testing these complex learning environments.

With the increasing automation in education and training, there's been a corresponding push to create semantically rich data, that is, to give the meaning to the underlying data elements—in ways computers (and other humans) can understand. The developers of xAPI, for instance, are attempting to build semantically rich usage profiles as well as published, shared vocabularies. Proponents of competency-based learning are attempting a similar feat, but in their case, to define the data elements that make up a human competency. Volunteers supporting the IEEE established a working group in 2018 to revise the decade-old Reusable Competency Definition (1484.20.1), expanding its utility and harmonizing it with other standards for competencies and competency frameworks.[90]

The working group's efforts are timely, as more formal education programs are embracing competency-based degrees, i.e., postsecondary programs where students earn diplomas by demonstrating mastery through real-world projects—rather than through time-based credit hours. In competency-based

programs, students are typically assigned learning coaches, rather than didactic instructors, and they have access to an array of open-source resources, including videos, textbooks, and online communities.[91] As of 2014, there were already an estimated 200+ competency-based learning postsecondary degree programs in the U.S., but policy regulations are lagging.[92] It's not clear how this trend will resolve, but we fully expect the core concept expand in the coming years.

Like competency-based degrees, micro-credentials, and the associated technology standards for digital badges, have garnered growing attention. Training and education credentials, such as licenses and diplomas, have existed for centuries as a way to verify someone's educational pedigree. Like their more robust cousins, *micro*-credentials assert that a person has demonstrated a particular competency. Unlike more formal credentials, however, learners can receive micro-credentials for smaller learning segments, and (at least hypothetically) micro-credentials reflect the performance-based approach of competency-based learning. Whether micro-credentials catch on remains to be seen. Practical and policy challenges still face the field; although, organizations such as the Lumina Foundation, Digital Promise, and BloomBoard are working to overcoming them. Meanwhile some commercial organizations are charging ahead with their tiny certs, including Udacity's nanodegrees and edX's MicroMasters.[93]

Given these many technological inventions, the rise of learning analytics, surge in neuroscience research, and developing maturity of learning science, educators and instructional designers are forced to rethink their discipline as well as their own capabilities. If done correctly, the future of learning will look noticeably different from its Industrial Age ancestor. Correspondingly, some have embraced the concept of learning engineers—a new (and still forming) paradigm that describes the "instructional designer" of the future. In 2017, the IEEE created a working group, named the Industry Connections Industry Consortium on Learning Engineering, to help mature the idea, led

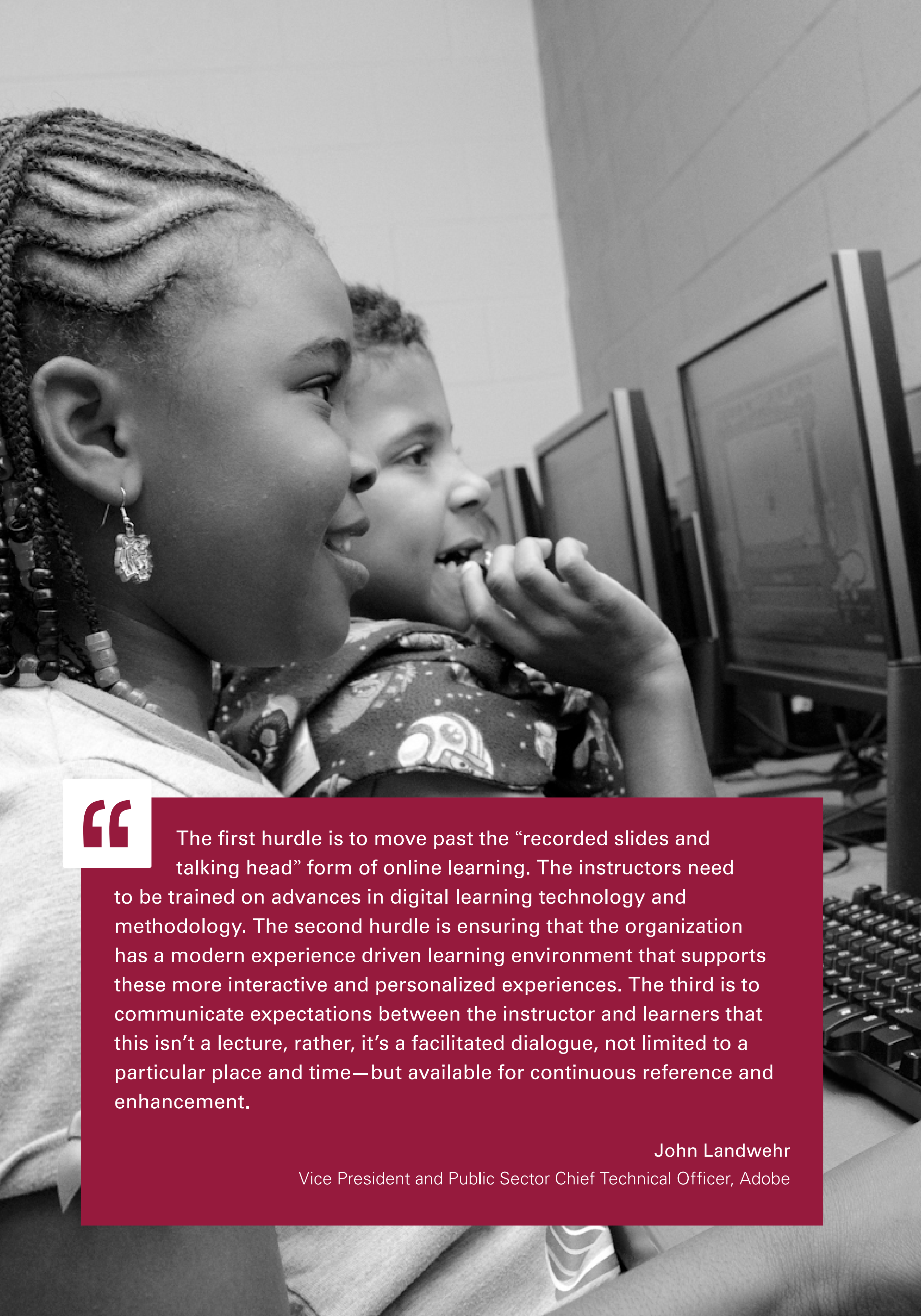
by Bob Sottilare, Avron Barr, Robby Robson, Shelly Blake-Plock, and others. In 2018, Chris Dede, John Richards, and Bror Saxberg released their guide to *Learning Engineering for Online Education*.[94] Saxberg, who also serves as a Consortium advisor and as vice president of learning science at the Chan Zuckerberg Initiative, described the emerging discipline:

> A Learning Engineer is someone who draws from evidence-based information about human development—including learning—and seeks to apply these results at scale, within contexts, to create affordable, reliable, data-rich learning environments.[95]

To add, from another of his quotations:

> There will come a time when we look back at how we "used to do learning," and, just as we now look at medicine in the 19th century, wonder how we ever made progress without using the science and evidence that we can now generate. We're not there yet—but we may be on our way.[96]

Saxberg's words ring true, not just for learning engineers but for the wider learning and development sector. Much has changed as technology advanced and learning science evolved. The concept of "distributed learning" has progressed, from its simple roots as a pragmatic tool to bridge the transactional distance, to today's cacophony of ubiquitous, adaptive, on-demand instruction. A central goal of the ADL Initiative and its larger community has always been to bring clarity and coordination to this discipline. Today, more than ever, the distributed learning community needs organizational, theoretical, technological, and policy structures to bring unity. We are, perhaps, in the middling ugly-duckling years of the field's maturation. The promise of responsive and evidence-driven ubiquitous learning is there, crafted by contributors for over 40 years. It's now our challenge to resolve the complexity, to bridge across its numerous facets as our connectivist peers have taught us, infuse deliberate learning theory into our work as learning science scholars advise, and, as the learning engineers promote, to embrace a comprehensive approach to enhancing the full continuum of learning.



"The first hurdle is to move past the "recorded slides and talking head" form of online learning. The instructors need to be trained on advances in digital learning technology and methodology. The second hurdle is ensuring that the organization has a modern experience driven learning environment that supports these more interactive and personalized experiences. The third is to communicate expectations between the instructor and learners that this isn't a lecture, rather, it's a facilitated dialogue, not limited to a particular place and time—but available for continuous reference and enhancement.

John Landwehr
Vice President and Public Sector Chief Technical Officer, Adobe

CHAPTER 3

DISTRIBUTED LEARNING INSTRUCTIONAL THEORIES

Scotty D. Craig, Ph.D. and Ian Douglas, Ph.D.

Learning has moved beyond the classroom. It's happening everywhere, all the time, formally and informally, incidentally and intentionally—and increasingly supported by digital technologies. For more than a decade, online education has consistently expanded.[1] The U.S. Department of Education estimates that 5.8 million students enrolled in distance education courses in 2015, the most recent year for which statistics exist, accounting for 28% of the total student population.[2] The Association for Talent Development reported that 88% of corporations offered e-learning as part of their workforce development in 2017, and 27% of high-performance organizations used e-learning for a majority of their training.[3] MOOC clearinghouse Class Central reported that MOOCs also grew, serving over 80 million students in 2017.[4]

Distributed learning should employ evidence-based practice, built on the science of learning

No doubt the impact of distributed learning will continue to grow; hence, educational decision makers, instructional designers and learning engineers, teachers, and trainers should understand the best practices for technology-enabled learning—and implement these to their best abilities and resources. This isn't just our opinion. For instance, the *Every Student Succeeds Act*, signed into law by President Barack Obama in 2015, requires that students in America be taught to highest academic standards and asks schools to employ evidence-based approaches to learning, supported by a scientific process that

provides evidence of effectiveness. Similarly, the World Bank, cited "acting on evidence to make schools work for learning" among their three priorities for 2018, writing "Act on evidence—to make schools work for all learners. Use evidence to guide innovation and practice."[5]

Building evidence and properly validating a theory within a scientific discipline, however, can take decades. Then more years to communicate its premise to the wider community—not withstanding those pockets who will inevitably resist the idea of evolution. Meanwhile, as this process plods forward, practitioners are anxious for improvement. So, they embrace theories that, on their face, seem to make sense, even if there's little proof to accompany them. Commercial interests further complicate matters, as companies are often quick to adopt popular theories, promote their unique value propositions, and build technology around them—all before adequate research has concluded.

But the world isn't so grim. The scholarly pursuit of learning science is increasing. The National Academies recently released a sequel to their excellent compendium, *How People Learn*. This new volume, *How People Learn II*, published near the end of 2018,[6] included new research on educational technologies, including findings on neurological processes, lifelong learning, and the impact of social and cultural factors. There's also growing awareness from policymakers and administrators of the importance of learning science and greater numbers of research programs at institutions such as the aforementioned Department of Education and World Bank.

In this chapter, we mix optimism with some healthy caution. In the next sections, we overview research that provides some guidance on designing for technology-supported learning and practical best practices for establishing associated design teams. We've omitted many quality theories, for the sake of brevity, but will summarize a few of the most relevant to the design of distributed learning. Our main goal is for readers to take away the ideas that distributed learning theories exist, authors have taken steps to make them accessible to practitioners, and new distributed learning systems—whether

concerned with the content development level or the enterprise infrastructure level—should be informed by this work.

INSTRUCTIONAL THEORIES

As outlined in the preceding chapter by Art Graesser and colleagues (Chapter 2), learning science theories have generally evolved with the zeitgeist of cognitive science. Early educational theories followed the behaviorist model, emphasizing drill-and-practice tactics, reward and punishment, feedback, and repetition. Cognitivist theories came next. In contrast to the behaviorists, cognitivists sought to understand the mind and apply principles of cognitive processing to the design of learning content. A third prominent paradigm, constructivism, followed. Constructivists argued that humans *create* rather than *acquire* information; it's therefore impossible for some "correct" understanding of the world to be transferred from one person's memories to another. Individuals must learn through engagement.[7]

As one might expect, each of these paradigms encouraged the development of various instructional theories. Seeing the proliferation of competing theories, Dave Merrill set out to evaluate and eventually harmonize the field. His resulting work, First Principles of Instruction, had wide impact.[8] For the first time, a framework incorporated the breadth of theories—and all within a concise set of principles. The inset below summarizes them, but we encourage readers to read Merrill's original article where he includes crisp guidance for instructional designers on each.

In *How Learning Works*, Susan Ambrose and colleagues followed in Merrill's footsteps.[9] They built on his First Principles and added to them new synthesized research on teaching. Their subsequent framework includes seven categories, each with several underlying recommendations written specifically for teachers and instructional designers.

1st PRINCIPLES OF INSTRUCTION (DAVE MERRILL)

Problem Centered – Engage learners in solving real-world problems

Activation – Active learners' relevant previous experience

Demonstration – Demonstrate what's to be learned (don't merely talk about it)

Application – Have learners use their new knowledge or skill to solve problems

Integration – Encourage learners to transfer new learning into their everyday lives

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Both Merrill and Ambrose et al.'s work recommends that practitioners create active learning environments. However, in practice, this suggestion is often watered down, distilled to superficial criteria like measures of classroom attendance or homework completion, or it's otherwise simplified to proxy indicators, such as attitude or interest. None of these truly meet the mark. As Michelene Chi and her collaborators have observed:

> In short, although "active learning" is a great idea for overcoming "passive learning," we have identified three concrete practical challenges that teachers may face when developing lessons that promote "active learning." First, broad recommendations such as *engage students cognitively*, *encourage meaningful learning*, and *get students to think about it* do not tell teachers how to create activities that overcome "passive learning." Second, teachers have few criteria to use in deciding which are the best "active learning" activities to design and implement. Third, there are no guidelines for teachers regarding how to best modify their favorite existing assignments in order to optimize "active learning." [10]

Chi and colleagues developed the Interactive, Collaborative, Active, and Passive (ICAP) framework to provide guidelines for fostering active learning environments. The ICAP categories describe hierarchical levels of cognitive engagement, with "passive" learning typically producing the weakest learn-

Seven principles for smart teaching from Ambrose et al.

1 **Learners' prior knowledge can help or hinder learning**

Teachers should talk with other instructors and use diagnostic tests of prior knowledge to learn about their students. Be explicit to students about the connection between new material and their prior knowledge; this aids long-term retention.

2 **How individuals organize knowledge influences how they learn**

It also affects how they apply what they know. So, make use of techniques that make knowledge organization schemes explicit, such as concept maps. Look for patterns of mistakes and misconceptions in learners' conceptions.

3 **Learners' motivation determines, directs, and sustains learning**

Help learners see the value in what's being taught and how it helps their future development. Provide authentic tasks with an appropriate level of challenge (simulations and games are useful). Get learners to understand the reasons for success and failure.

4 **Learners must acquire and integrate component skills**

To develop mastery, learners need to practice integrating component skills and know when to apply what they've learned. Be aware of expert "blind spots"—steps they perform unconsciously and are, therefore, not well-articulated in instruction. Provide isolated practice of component skills in diverse contexts and then facilitate the integration of component skills in more challenging tasks.

5 **Goal-directed practice with targeted feedback enhances learning**

Phrase instructional goals in terms of capabilities rather than knowledge (refer to Chapter 13, in this volume, on competency-based learning). Provide time for deliberate practice, and pair this with feedback that focuses on specific items that need improvement.

6 **The social, emotional, and intellectual context impacts learning**

Learner current development is influenced by the context. A positive and constructive tone of communications within the learning community often improves learners' motivation and behavior.

7 **Students must learn to monitor and adjust their own learning**

Help learners develop metacognitive skills, such as self-monitoring. A malleable, rather than fixed, perspective of intelligence can also be promoted and has been found to influence performance.

ing outcomes and "interactive" learning often promoting the strongest. Interactive learning encourages learners to actively integrate new and prior knowledge, draw inferences to fill knowledge gaps and confusions, and otherwise enact strategies that build rather than merely rehearse knowledge, ultimately supporting deeper learning and increased transfer to new domains. Notably, this research highlights that it's the way learners engage in different activities that makes them more or less passive; learners' engagement levels aren't necessarily "cooked in" to the instructional interventions, themselves.

Example of "watching a video" at various levels of engagement:

PASSIVE Receiving	**ACTIVE** Manipulating	**CONSTRUCTIVE** Generating	**INTERACTIVE** Dialoguing
Watching the video, without doing anything else	Actively engaging with the playback, such as rewinding and pausing; taking verbatim notes	Explaining concepts from the video; taking paraphrased notes; contrasting the video to other materials	Debating with a peer about the message in the video; actively analyzing the position of the video in a small group discussion

Example application of Chi and colleagues' ICAP framework

Much of our preceding discussion has emphasized the science of teaching or the practice of instructional design. However, as Ambrose and her coauthors highlighted in their own work, recommendations on designing and delivering *instruction* miss more than half the equation. Though tightly bound, *learning and development* are wholly different phenomena from *education and training*. With this understanding, Ambrose et al. highlighted three critical components of learning:

1. Learning is a process, not a product.
2. Learning involves changes in knowledge, beliefs, behaviors, or attitudes, which must unfold over time.
3. Learning is not something *done to* others, but rather something learners must do themselves.

Teachers, trainers, and instructional designers can't directly manipulate

what's happening in learners' minds, but some theories give guidance on how to encourage better learner processes.

Self-regulated learning theory, for example, describes learning processes guided by the learner him- or herself and which is, at least partially, intrinsically motivated. At its most basic, self-regulated learning involves planning, executing, and then reflecting on some activity. Hence, it involves the application of metacognitive knowledge and monitoring skills, such as understanding different cognitive tactics and correctly identifying the difficulty of different tasks.

Louise Yarnall and her colleagues describe self-regulated learning in more detail later in this book (Chapter 15). In short, one way to envision it is as a cycle, involving different phases that someone undertakes to strategically and intentionally improve performance.[11] These phases start with *task definition*, where someone works to understand the problem at hand along with any available resources. This is followed by a *goal setting and planning* phase, where learners establish objectives and select tools and strategies to meet them. Next, an *enactment or engagement* phase occurs, where learners implement their chosen strategies and attempt to perform the task. Finally, there's an *evaluation or adaptation* phase, where learners assess their actions and outcomes, and revise their goals, plans, and strategies, accordingly. Although these actions are, by definition, learner driven, individuals without strong metacognitive skills can be taught. For instance, teachers and trainers can provide scaffolds to help guide learners through these self-directed learning processes.

In closing, this section has offered the barest summary of instructional theories. Some other sources serve as useful supplements. Harold Pashler and colleagues published seven principles for instructional strategies, including recommendations for spaced learning, using worked examples in combination with problem solving, combining graphic and verbal descriptions, integrating abstract and concrete concepts, using quizzing and questions to eliminate misconceptions, and supporting self-regulated learning by helping learners

allocate study time.[12] Art Graesser built on prior work to define 25 principles of learning (clearly an overachiever in learning frameworks!).[13] These roughly group into recommendations for reducing processing load, facilitating learning by implementing strategies within (e.g., feedback and deep questions) and around the learning content (e.g., testing effects and spaced learning), and suggestions for helping learners understand the process of learning (e.g. self-regulated learning and desirable difficulties). Finally, for a truly comprehensive historic treatment, Peter Jarvis authored a three-volume set, beginning with the book, *Towards a Comprehensive Theory of Human Learning.*[14]

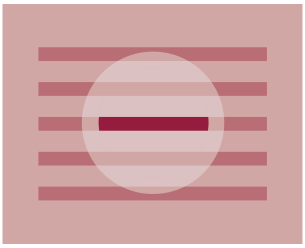
INSTRUCTIONAL TECHNOLOGY THEORIES

Technology, by itself, doesn't solve problems in training and education—technology needs learning science principles!

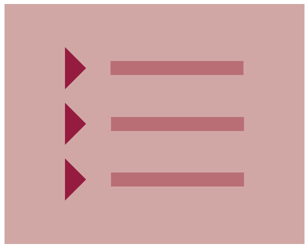
Classic instructional theories emphasize learner-content, learner-teacher, or learner-learner interactions. Starting in the around the 1960s, researchers began to also examine learner-interface dynamics, leading to unique pedagogies for educational technology. Early work on instructional media involved comparison studies, often looking at technology-mediated versus traditional settings. These found "no significant differences," but this was the behaviorist era and (as described below) instructors tended to employ the instructional media in the same way they might deliver traditional teaching. In the 1980s, with growing interest in the cognitive perspective, researchers began to look more closely at media attributes and their interactions with individual differences.[15]

Coming out of this growing appreciation of instructional technologies, Richard Mayer published his highly influential *Cognitive Theory of Multimedia Learning*. Multimedia learning is a combination of more than one modes of information presentation, such as visual images with a narration, within a

MAYER'S 12 PRINCIPLES OF MULTIMEDIA LEARNING

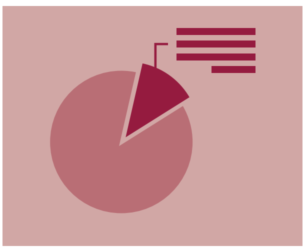


COHERENCE
eliminate extraneous information

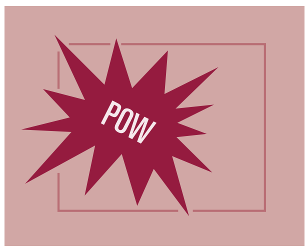


SIGNALING
highlight essential information

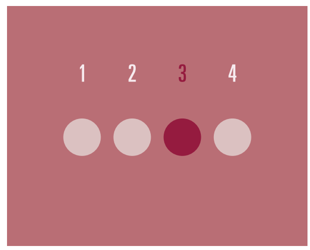
REDUNDANCY
use graphics and narration (not on-screen text)



SPATIAL CONTIGUITY
put words and related pictures near each other

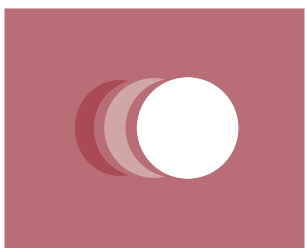


TEMPORAL CONTIGUITY
show words and related pictures simultaneously



SEGMENTING
present lessons in under-paced segments

MULTIMEDIA
words + pictures are better than words alone



MODALITY
use graphics and narration versus animations and text

PRE-TRAINING
start lessons with a quick refresher and an overview

PERSONALIZATION
use a conversational style, not a formal one

VOICE
narrate in a friendly human (not machine) voice

IMAGE
the narrator's image isn't needed on-screen

> …education doesn't educate you unless it changes you.
>
> **Betty Lou Leaver, Ph.D.**
> Director, The Literacy Center; Manager, MSI Press; Former Provost, Defense Language Institute Foreign Language Center

learning environment. Mayer's theory builds on core cognitive mechanisms. For instance, it acknowledges the limited capacity of working memory, assumes that learners have two cognitive processors that handle new information differently (an auditory and a visual processor), and that learners must be cognitively engaged to produce new knowledge structures.[16]

Recommendations for technology-enabled instruction naturally followed from these tenets. For example, given the limits of working memory, multimedia learning materials need to moderate the amount of essential processing required by the learners depending upon their prior knowledge, experience, and competencies. Furthermore, given our brains' two processing channels, complementary information should be delivered simultaneously to both to more efficiently support learning. Many other design principles can also be derived; these cluster under 12 principles, as summarized in the adjacent graphic.

Another uniquely technology-centric theory is described by the Substitution Augmentation Modification Redefinition (SAMR) model, popularized by Ruben Puentedura.[17] It emphasizes a unique challenge with learning technologies; that is, often people use them in similar ways and assume similar context to traditional, formal education settings—with classrooms, instructors, a fixed body of content to be learned and a fixed amount of time. This model helps explain why, for instance, the first web-course designers attempted to recreate printed texts online or why the original virtual classrooms took so many cues from physical ones.

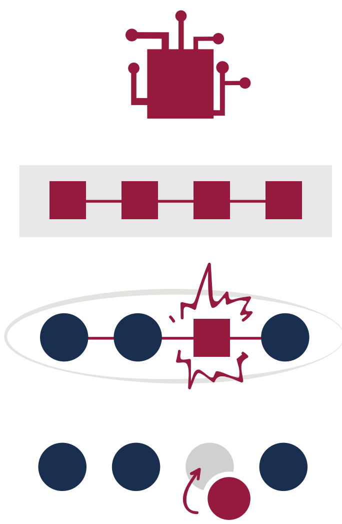
The SAMR model defines levels of technology use in teaching and learning. The most basic, and most often implemented level is *substitution*, where the

technology is used to perform the same task as was done before. For example, an instructor uses PowerPoint to replace acetate slides or students use laptops to replace paper notebooks. Alternatively, the highest level is *redefinition*, where technology supports new learning tasks that were previously inconceivable. This level represents the future of learning and is a foundational reason for reimagining instructional design.

Technology is changing the way we live, and future instructional technology theories should reflect new approaches to learning, including in individual, social, and lifelong learning contexts. However, many of our current best practices were developed before this digital explosion, leading us to ask, "How will we transform our current models for learning and not just consider how we make incremental improvements to the traditional approach?"

SAMR

The SAMR model highlights our tendency to use new technologies in old-school ways.



REDEFINITION
Technology enables new tasks, previously inconceivable

MODIFICATION
Technology enables significant task redesign

AUGMENTATION
Technology acts as direct substitute, *with* functional improvement

SUBSTITUTION
Technology acts as direct substitute, *with no* functional improvement

★ There's too much emphasis on 20th century (pre-internet) instructional models. Need to REDEFINE (not just substitute for) legacy training and education!

VISION FOR THE FUTURE OF LEARNING THEORY

One challenge with learning theories is that they're prone to focus just on the design, delivery, and evaluation of instruction. Even with additional consideration for technologies used for learning, we're still omitting part of the puzzle. Earlier in this book, Walcutt and Schatz outlined six elements that need to be considered for the future learning ecosystem: technology infrastructure, design, commitment, governance, policy, and human infrastructure. The construction of learning elements—including those theories covered so far in this chapter—fall into their "design" category. Undoubtedly, the careful design of learning content, associated delivery and evaluation techniques, and learner-support methods are critical. However, the other elements in this also framework warrant consideration.

Certainly, Walcutt and Schatz aren't the first to suggest a wider aperture. Badrul Khan,[18] for instance, proposed an eight-dimension framework for e-learning, comprised of institutional, management, technological, pedagogical, ethical, interface design, resource support, and evaluation factors. Shahid Farid and colleagues built on Khan's work.[19] They use empirical data from stakeholders about roadblocks to e-learning in postsecondary environments. Farid et al.'s model includes software, technical, institutional, personal, and cultural dimensions. Beatrice Aguti and her colleagues also developed a broader model for higher-education contexts, but this time for blended learning. Their framework has four dimensions, including e-learning course delivery strategies, e-learning readiness, quality e-learning systems, and effective blended e-learning.[20] For our purposes, we're less concerned with the potential similarities and differences of these various frameworks. Our point is simply that learning—and particularly technology-enabled learning—happens within a broader context.

From this broader perspective, it's clear successful distributed learning enterprises will rely up-on interdisciplinary, effective teams of practitioners. Where teachers once presided over their classes or principals over their schools, the emerging learning ecosystem has less defined boundaries, and it also relies upon a greater diversity of expertise (as described in more detail in Chapter 19, which discusses learning engineers).

> Take care to avoid the **Everest Syndrome**—the urge to embrace new instructional technology just because it's there

Successful, future (distributed) learning will be developed by organizations able to build and support multidisciplinary teams. For instance, in lieu of an isolated instructor, we could imagine a team of three to five members working together to develop learning experiences. This team might involve an instructor or content expert, an instructional design or learning science practitioner, a technology expert, and perhaps even a data scientist. Additional members, such as usability experts and psychometricians, might also be required.[21] Finally, to be truly successful, there needs to be a larger learning organization (administration) in place to facilitate interactions and coordination.[22]

This new team structure will also require strong leadership.[23] Leaders responsible for learning will need awareness of the expertise available to them and know how to integrate different kinds of expertise into learning development processes. They'll need to understand evaluation, at multiple levels (such as within the content, to assess learners, but also at an institutional level to evaluate the learning experience, itself), and they'll need to consider broader implications, such as privacy, ethics, and social factors. During learning design and development phases, leaders will need to look for efficiencies. For instance, they'll need embrace the reuse of learning materials, looking for ways to reduce the cost of development efforts by reusing already developed content elements, technologies, or tools.

Thus, learning leaders should continually ask themselves questions, such as:

- Do we have all the specific expertise on our team to meet our goals?
- Is the team working effectively as a community with shared purpose?
- Are we making good use of existing reusable resources and tech?
- Are our evaluation processes (at all levels) the best we can achieve?
- Are we aware of the evidence in support of each instructional resource, method or technology we use?
- Do we have someone capable of interacting with the output of the learning science community to identify relevant knowledge that can be adapted into our process?

The development of instructional materials has sometimes been compared to software development.[24] The development of software in the early days of the personal computer involved one or a few individuals crafting an application with a primary focus on function; however, modern software development involves large teams of different specialists (e.g., software architects, software engineers, user-experience designers, cybersecurity specialists) working together and collectively considering a broad range of design attributes (e.g., functionality, security, aesthetics, usability). Modern software developers are also comfortable with the idea of reuse and "mashups" (combining data or functionality from different sources). Numerous repositories of reusable code are readily available on the internet. Also, connections called Application Programming Interfaces (APIs) allow different operational software platforms to share data across them, enabling sophisticated functionality, such as Google maps, or up-to-the-minute data, such as from the U.S. Government's data.gov, to be embedded in any other application. However, the same ethos isn't always found in modern instructional development—both the organizational dynamics of multidisciplinary instructional teams and the infrastructure needed to share and integrate learning materials need to be cultivated.

However, promoting successful interdisciplinary teams is challenging, not because adequately skilled individuals are unavailable but because they often

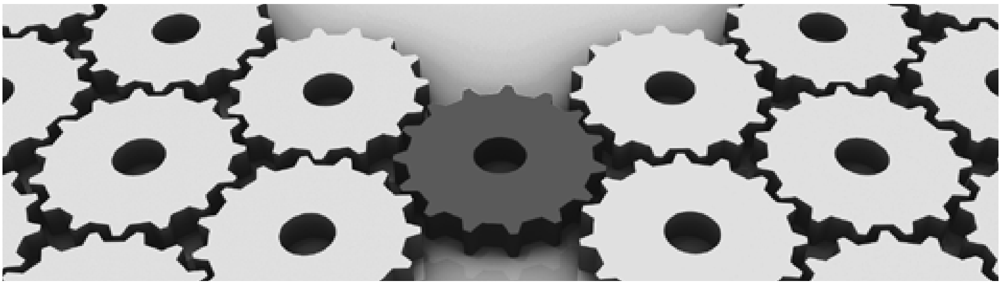
≈**90%** ...of **students were highly engaged**, when taught via well-designed, service-learning methods

Projects That Work is an ongoing research study with the goal to provide teachers data-driven information to make decisions to use service learning flexibly, efficiently, and effectively. The premise is that if schools and teachers have continuously updated lists of projects that were highly rated by 20 or 25 previous classes around the country, these projects would (a) be known to teacher and (b) could be replicated, providing all students the opportunity to realize the potential of what service learning has to offer....Preliminary findings revealed that about 90% of students were highly engaged by service learning and produced positive results from many types of service learning projects. Many of the findings to date echo prior research demonstrating the role of well-designed programs that include specific activities to prepare students with a clear and compelling rationale for the project and with specific roles and responsibilities. The key to replication in schools with less expertise in service learning may focus on teachers having information on key components of projects. It's important to ensure that the projects are feasible for teachers and students to do, and that they lead to students' belief that they're making a difference and perceive that they're learning.

Edward Metz, Ph.D.
Projects That Work

lack teamwork and collaboration skills—skill which learning professionals are rarely taught explicitly.[25] Thus, a key step towards achieving the future learning ecosystem will involve the maturation of organizational processes, teamwork-focused professional development for various contributors, and a culture shift—similar to one that happened within software engineering.[26]

On the content-sharing side of the equation, we've already seen significant efforts to encourage reuse in instructional development, but so far, these have met with limited success, particularly compared the level of reuse and data-sharing that happens in software development. Roughly two decades ago, SCORM was developed to help facilitate learning content reuse, and there



We used AutoTutor for the Office of Naval Research and put it into ALEKS, a commercial adaptive learning system. It went ok, but then we tried to do a scale-up in a school district. We were able to get a big teacher preparation session. They were reasonably optimistic. The strategy was to let them use ALEKS on their own before getting AutoTutor. We found that initially a lot of people liked it, but then they had school vacation and then after that they had a huge snow storm and were out for about 8 days of schools. Then they had a very short time for standardized testing for the state (about 5 weeks) that resulted in universal attrition. In talking with the teachers, they had to teach to the test, but ALEKS is based on mastery learning. It won't allow you to do topics you're not ready for.…From a learning perspective, it makes sense, long-term, but teachers have many logistical needs that aren't directly represented in adaptive systems. They have to have the kids know information/knowledge at a certain time whether or not the student is technically ready for it—even if they aren't going to remember it. Their knowledge repository might collapse later because they didn't get the foundational information when they needed it but it's what they needed for the test.

Benjamin Nye, Ph.D.
Director of Learning, Institute for Creative Technologies,
University of Southern California

have been multiple attempts to build repositories of reusable educational resources, such as the MERLOT.[27] Another, more recent repository, the Open Educational Resources Commons,[28] offers curated content with open licenses; it also encourages co-creation and participation by users.

Newer repositories are now integrating evidence in support of the assets provided to the community. The What Works Clearinghouse from the Institute

of Educational Sciences at the U.S. Department of Education is one example of a research-evidence repository.[29] This clearinghouse identifies studies with credible and reliable evidence of effectiveness, and it disseminates free reports and summaries on its website. The What Works Clearinghouse currently has over 700 summaries on effective educational innovations and over 10,000 reviewed studies available in its repository. A number of similar government-sponsored research communities can also be found, such as CLEERhub[30] for National Science Foundation research on Engineering Education; the National Academies Press, with open-access e-books on hundreds of topics, including Behavioral and Social Sciences and Education;[31] and the Defense Technical Information Center for military-funded research.[32]

CONCLUSION

In summary, extensive research has been conducted to inform instructional theory, but there continues to be a gap between scholarly findings and their practical application. However, there are many excellent resources for teachers, trainers, instructional designers, policymakers, and administrators. Unfortunately, many of these resources still assume that learning will occur under traditional (Industrial Age) conditions; so, consider them with caution. Some theories have been developed specifically with instructional technologies in mind. Seek these out, but also remember it takes years to properly validate a theory; so, watch out for hype, particularly when commercial profits or someone's reputation is on the line. Also, when designing for technology-supported learning use a measure of creativity, to avoid succumbing to the "just substitution" mindset. Similarly, also be willing to rethink the design, delivery, and coordination of learning processes. Emerging technologies are radically changing the ways we train, educate, learn, and develop, and they're similarly changing the ways learning professionals operate—embrace teams, seek out shared materials, and embrace a culture of reuse.

> Education in the future will be more of an iterative process. Currently, people pursue their education at the beginning of their lives and then they go to work. Education beyond that initial period typically only happens because of some disruption in their lives—they lose their job or other changes in circumstances. It's difficult to access at that stage in life, but in the future, while you'll still have early-life education, it might look a bit different—with more of an emphasis on work-ready skills and learning to continuously learn. There will also be many more opportunities for dipping in and getting back out of the workforce throughout someone's life. Education will be more just-in-time and based on the needs of the moment. Technology will support that, but it requires significant change in the way education institutions operate and the way employers do things.

Martin Kurzweil, J.D.

Director of the Education Transformation Program, Ithaka S+R

CHAPTER 4

LIFELONG LEARNING

J.J. Walcutt, Ph.D. and Naomi Malone, Ph.D.

The world has progressed in so many ways over the past 100 years, yet our educational structures have stayed relatively unchanged. Incremental progress has certainly occurred, to include improvements in classroom organization and information delivery, but the developmental models, progression of formal educational offerings, and recognition of learning via grades and degrees have proven resistant to change. As a society, we still focus on controlled settings for learning and group-based information delivery. The sequence is linear, the instruction is split into finite end-points, and the whole process is assessment-oriented.

We rely on outmoded developmental models (such as Jean Piaget's stages of cognitive development) and use a failure-focused mindset when measuring learning, that is, students' developmental speed and depth of knowledge are judged against expected averages, largely defined by age-based phases. In a K–16 setting, those who fail to conform to expectations are "behind in their development," and in workforce or military settings, those who lag are judged as incapable, unmotivated, or possessed of other character flaws. We assign grades based on achievement and determine progression through the system based on time factors, such as credit hours or classroom attendance, along with single-point, high-stakes testing. Similarly, we make strategic-level curriculum decisions based on these goals, such as how to achieve increased seat-time or time-on-task, assuming that more time spent learning will result in improved outcomes (even though data suggest that students need non-instructional assimilation time and varied experiences to aid comprehension, and that learning needs to be context-based).[1]

In the modern world, we're inundated with unlimited, unfiltered, and unmanaged data; individuals can learn anything they wish, but we run the very real risk of increasing low-level information acquisition to the detriment of higher-order comprehension.

We largely place students in controlled settings (classrooms), where information is filtered by a teacher or curriculum designer to ensure its accuracy and intelligibility, where goals are clearly defined, the level of information provided is appropriate for learners, the pace is controlled, and someone is available to help monitor the informational content and its delivery. In many ways, this is where we've seen improvement in learning over the last century. Many of the advancements in instructional theory have focused on formal learning experiences, and teachers and administrators made efforts to bring those findings into the classroom.[2]

However, learning isn't confined to the classroom. The world outside the schoolhouse is filled with limitless sources of potential learning. We're increasingly exposed to torrents of data, questionable "facts," and diverse unconnected information. It's incumbent upon the individual—the learner—to determine the value of that information and how it connects to other data or experiences. The speed and diversion of information in our modern world impacts our abilities to synthesize useful knowledge, effectively retrieve it, and translate or apply it in practice.

Information overload is a significant and growing issue; volumes of data are bombarding people at faster and never-ending rates. When exposed to too much data, the human brain will tend to focus on the clearest, easiest to understand, most familiar elements—and discard the rest.[3] It's the body's natural way of functioning in a focused and emotionally stable state. However, in today's data-rich climate, this sometimes means retention of false or misleading information, which can lead to poor decisions at both individual and collective levels. Thus, as the world continues to become increasingly volatile, uncertain, complex, and ambiguous, we need educational practices that ensure people are prepared, not only for today's classroom but for tomorrow's global landscape.

That preparation doesn't end at 18 or 25 (or even 100!) years of age. With increasing average lifespans[4] and worldwide pace of change, continuous lifelong

learning has become a necessity. New inventions create or destroy whole industries each year, and AI is altering the nature of work in fundamental ways; add to that increasing lifespans and the evolving view of employee-company permanency. All this means that many people will change careers—not just jobs—multiple times within their lives.[5] Thus, we need to expand the timeframe of learning beyond K–12 and even beyond traditional higher education and vocational schools. While these forms of formal, developmental education are likely to persist for some time, we can expect more learning to occur later in life—in the 30 to 65 age range.

It's time to change course by moving away from incremental improvements to our existing education system and instead, reimagining how foundational scientific principles can inform a new model of learning—one that spans the lifetime.

LIFELONG LEARNING VISION

Our vision for lifelong learning takes a more naturalistic perspective, acknowledging that learning is pervasive. It happens all the time and everywhere, in the classroom, online, at home, and through lived experience. Learning is personal, changing in form based on the unique personality, interests, skills, attributes, circumstances, and beliefs of each individual. It's fluid and nonlinear. Various subjects don't exist in distinct and disconnected packages; instead, diverse concepts that can be learned together. It's flexible. People can achieve success in countless ways via individualized learning trajectories that maximize their unique potential, rather than boxing them into a finite set of "accepted" developmental boxes. It's holistic. Future learning experiences will reach beyond the cognitive domain to emphasize the whole person, including

	INDUSTRIAL AGE PAST	FUTURE
FOCUS	Mastery of knowledge and skills (mostly cognitive and psychomotor)	Holistic development across facets, merging cognitive, physical, social, emotional, and so on
EDUCATOR	Expert authority figure; learning designer and director	Facilitator, mentor, and coach, within a larger, connected network
EXPERIENCE	Mostly structured, often passive and linear, with summative assessments	More personalized and active, with a greater formative focus
TIMING	Discrete, episodic, largely age-based (K-12, higher education, career training)	Continuous lifelong learning, integrated across experiences
ACCESS	Limited access choices, usually either in a face-to-face setting or online	More diverse and blended choices, truly enabling “anytime, anywhere”
TECHNOLOGY	Dedicated systems in silos, often focused on formal learning	Distributed systems-of-systems, an interconnected ecosystem

their social, emotional, and physical development. Education will be designed to help cultivate people who can thrive in a complex and chaotic future, rather than simply ushering them through the linear, K–12 milestones we have today.

4 KEY TENETS: LIFELONG, HOLISTIC, UBIQUITOUS, AND ASSET-FOCUSED

Our lifelong learning model includes four main principles. First, as its name implies, it considers learning a continuous, lifelong experience. Today, we tend to view learning in discrete developmental phases—early childhood, then K–12, and, finally, higher education or workforce training. In the future, we'll view learning as an ongoing process, where information is constantly synthesized, all the time and from copious sources. The second tenet of this model is that learning isn't constrained to cognitive development. Rather, we must recognize learning as an interplay among cognitive, social, emotional, and physical skills, attributes, and capabilities. Third, learning involves a mix of formal, nonformal, and informal activities. Today, we primarily measure and accredit knowledge and skills acquired in formal settings and assessed within similar structures. However, in the future, life experience and independent, informal learning will also be measured and recognized as much as—or, in some cases, more than—formal learning. As our capacity to measure learning and experience improves, we'll also be able to examine individuals' experiences more systematically, to better understand what they know, comprehend, and are capable of achieving. Finally, this is an asset model, not a failure model. This means learners of all ages are viewed through a lens that considers where they are today and where they'll grow to tomorrow.

Each of these tenets is described in more detail below.

OECD LEARNING FRAMEWORK 2030

WWW.OECD.ORG

The *Learning Framework 2030*, from the Organisation for Economic Co-operation and Development, defines a vision and underlying principles for future of educational systems. Still a work-in-progress, the framework is being developed by a community of experts, school networks, teachers, students, youth groups, parents, universities, local organizations, and social partners. Its vision is to help every learner develop as a whole person, able to fulfill his or her potential and contribute to worldwide wellbeing. The current version of the framework emphasizes:

- New solutions for a rapidly changing world with diverse global challenges
- New transformative competencies for innovation, responsibility, and awareness
- Learner agency—the responsibility for one's own education throughout life
- A new, broad set of desired knowledge, skills, attitudes, and values
- Individual and collective educational goals for wellbeing
- Design principles for eco-systemic change

1. Learning is lifelong

Although 90% of brain volume is attained by age 6, learning occurs across the lifetime and continues to affect the brain's capabilities. Certainly, early childhood experiences impact individuals' ability to compensate effectively as they age.[6] However, research on neuroplasticity demonstrates that the brain can reroute information and make up for trauma due to brain injury. Essentially, people can gain or regain skills otherwise lost during the trauma.[7] There's also significant evidence that neural development continues throughout the lifespan.[8] Although cortical thickness, mass, and connectivity seem to decrease with age, adults can compensate by activating interdependent neural mechanisms gained from life experience. In other words, although the brain develops most rapidly in childhood, learning can effectively occur throughout

life and is shaped by individuals' behaviors.[9] What and how much individuals learn depend on a variety of micro- and macro-level factors. Micro-level factors include individual choices, motivations, and the ability to self-regulate, particularly outside of formal education settings. Macro-level factors include learners' neighborhoods, societies, and cultures.

Some of these factors make adults particularly well-suited for learning. Clarity of interests and goals, and greater self-awareness make this time-frame conducive to personal growth and often encourage a greater motivation to learn. Adults also have a greater wealth of experiences to draw upon, which can help them synthesize new information more deeply and efficiently.[10] However, placing the control of learning into adults' own hands may encourage them to focus too narrowly on limited, task-specific forms of learning. We'll need structures that protect and support a comprehensive view of learning. Otherwise, we risk having deep experts embedded within stovepiped knowledge communities who lack a general understanding of how the pieces fit together to work within a holistic, efficient system.

2. Lifelong learning must encompass whole-person development

The ability to effectively participate in life is not exclusively determined by one's cognitive abilities or educational attainment. Rather, resilience, motivation, circumstance, exposure, metacognition, self-regulation, and other personal attributes contribute to a person's ability to navigate life. This position is strengthened by the finding that "brain development and cognition (and the connectivity between cortical areas) are influenced and organized by cultural, social, emotional, and variability in learning."[11]

In other words, whole-person development necessarily incorporates cognitive, social, emotional, and physical capabilities and these are, in turn, influenced by cultural systems.

We're training people for jobs that aren't going to exist anymore.

James Robb

Rear Admiral, U.S. Navy (Ret.)
President, National Training and Simulation Association

Harvard's 60-Year Curriculum initiative encourages a new paradigm of thinking about learning and the education process. It recognizes that people learn throughout their work lives—and often beyond, into retirement.

"It's just a subset of the larger territory that we're looking at; it's an under-appreciated subset but important for our economy and civic health. We need to recognize that the world is changing and that we don't leave people out to dry because their first career fizzled out and dried, and we didn't have a mechanism to help them out. Under the spotlight, we have K–12, higher education, and retirement, but when you have a career change and the world isn't helping you, it's murky. We held a conference recently focused on the concept of education ages 15–75. We asked, "How do we make that a different span of life during which people feel supported? Do we need unemployment insurance?" We're interested in figuring this out. For example, what if I'm really struggling and I don't know if I want to be a researcher or a designer? The real question now is what do you want to be first? We didn't have those dialogs in the past; it's totally different now.

Christopher Dede, Ed.D.

Wirth Professor in Learning Technologies
Harvard Graduate School of Education

We will need new models of learning and theories of development to effectively address the "whole-person" learning paradigm. To date, much of the human-development has focused on the early stages of life (prior to adulthood). As we move away from a front-loaded notion of education and towards a lifelong learning concept, we'll need to expand this body of research to incorporate adult learning, changing societal conditions, and the goal of developing more holistic capabilities across time and space.

COGNITIVE DEVELOPMENT

Although mature theories of cognition and learning already exist, these will need to be expanded and potentially reevaluated within the future lifelong learning model. Discussions of cognitive development usually point back to the foundations built by Jean Piaget (1936) and Lev Vygotsky (1978).[12] Piaget's theory of cognitive development defined four critical periods in which a young child develops sensorimotor intelligence, preoperational thought, concrete operations, and, finally, formal operations. Interestingly, the final stage spans ages 11 to adulthood. People who reach this final stage (and not all do, according to Piaget) are able to think abstractly. Since we now know that learning occurs throughout an entire lifetime, what happens after reaching this stage? Vygotsky's sociocultural theory of cognitive development offers some answers; it focuses on a person's journey to individualized thinking through a co-constructed process of social and cultural interaction. Therefore, the individual learns either by using self-regulatory tools (e.g., self-speech) or by observing and/or taking direction from others. Though both Piaget's and Vygotsky's theories recognize the interplay between self-development and directed learning, they take some opposing views; neither accounts for development across the lifetime, and neither consider how a person can achieve a set of meta-skills across disciplines, experiences, and formal and nonformal learning.

Further, technology is changing the nature of human cognition. We can now offload data storage and "lower-order" cognitive tasks to computers, aggre-

gate and analyze large sums of information as never before possible, and access content ubiquitously. These affordances create the opportunity to exponentially accelerate human cognitive development, both in time and scale. For example, if human brains have finite working memory capacities,[13] then computers can expand this—to not only enable humans to work with more information (without task shedding) but to also better digest and comprehend wider amounts of information simultaneously. As another example, since humans are highly influenced by life experiences and a computer can provide opportunities to experience simulated situations, we can expand our store of experiences in significantly shorter amounts of time, benefiting from what might be called "unlived experiences."

> "Key hurdles in developing today's students to be ready for life include a lack of early childhood experiences and foundational language that can serve as a springboard for later learning opportunities. Expectations are not always where they need to be, from teachers or leaders; consistently higher expectations are needed.
>
> **Nathan Oakley**
> Chief Academic Officer, Mississippi Department of Education

Computers are augmenting human cognitive development, not merely by increasing access to information but by also affecting our brains structurally and neurologically. Across its lifetime, the brain will continue to develop and learn but also, as new generations are born, they will increasingly have the benefit of access to accumulated knowledge and experiences of those who came before. In a twist of irony, while the stage theories of Piaget and Vygotsky have been overcome, the basic belief that cognitive development as a mixture of human natural capacity building and social-historical influence remains correct. What they didn't foresee was the expansion of capabilities that human-computer interactions could achieve.

WE AREN'T BUILDING RESILIENCE IN AMERICANS ANYMORE.

It starts with little kids, as little as 6 months old. We used to give them a spoon and a pot, and they were creative with what they had. Now they're given little kid toys—each toy has one function. These toys have pre-thought goals, and by providing them, we're taking away kids' creativity. Resilience is not fortitude; it's the creativity to find your way out of a hard situation. It also isn't singular; it's social and emotional. We can hide feelings but that's uncomfortable. Instead, we have to learn that emotions should be managed; there are times we should be mad and times we shouldn't, and we should know the difference.

Betty Lou Leaver, Ph.D.

Director, The Literacy Center; Manager, MSI Press; Former Provost, Defense Language Institute Foreign Language Center

SOCIAL DEVELOPMENT

Like cognitive developmental models, the lifelong learning paradigm obliges that social developmental theories be expanded. Social development researchers have primarily studied younger ages [14] or special needs populations.[15] No doubt, developing social skills in young people is a worthy goal; however, researchers have focused on these populations while sparing much less attention for older populations and lifelong social learning. A body of research does

exist around interpersonal employment skills, but social tendencies, changes, growth, and goals across the lifetime require more attention.

A recent 20-year retrospective study in the American Journal of Public Health found participants with higher "social competence" characteristics, such as sharing and cooperating, were more likely to have higher education attainment and better-paying jobs.[16]

In the lifelong learning model, there's an expectation that formal education will evolve to encompass these skills, in both the formative and later years of life. Additionally, we expect that resumés will acknowledge these skills in the future. If we're going to reframe our focus from creating workers to developing whole persons—individuals who can be successful across life experiences—social skills figure prominently into the holistic model. That means not only understanding lifelong social skills and finding ways to cultivate them but also rewarding individuals who possess them.

EMOTIONAL DEVELOPMENT

A prominent model of emotional development, developed by Carolyn Saarni, measures emotional competence as a set of affect-oriented behavioral, cognitive, and regulatory skills people develop over time within their social environment.[17] These skills include individuals' awareness of their own emotions, ability to discern and understand others' emotions based on situational and expressive cues, and capacity to cope with distressing emotions using self-regulatory strategies. Similar to Piaget's and Vygotsky's models, Saarni's model uses phases to categorize the developmental process, and it only addresses development from early childhood to adolescence. Moving toward a lifelong learning model of education requires more research on adult emotional development as well as the impact of individuals' emotional wellbeing (e.g., mental health, and ability to deal with stress) across all ages.

The Collaborative for Academic, Social, and Emotional Learning,[18] a not-for-profit dedicated to enhancing social and emotional learning, recommends a more robust model that integrates intrapersonal, interpersonal, and cognitive competence. It includes five key areas that encompass various behaviors, mindsets, strategies, and skills:

- *Self-awareness*, such as accurate self-perception and self-efficacy
- *Self-management*, for instance, impulse control
- *Social awareness*, including empathy and respect
- *Relationship skills*, such as teamwork and communication
- *Responsible decision-making*, including reflection and ethics

Research suggests that early emotional regulation skills have a significant impact on development and outcomes in later life.[19] For example, emotional regulation is part of the spectrum of skills needed to be successful in the classroom. The emotional regulation and interpersonal strategies children develop in early years allow them to navigate the school system, and more than that, these skills become key tools for success in life—arguably more than the academic knowledge itself. But can these skills be taught? Substantial evidence exists[20] that suggests: *yes*. Explicit teaching of social and emotional skills

There's a significant **emotional impact of constant change** and intellectual learning required for a multi-career expectation. We're living in constant acceleration, and we're trying to keep up with it. So, the question is: *What's the foundation we need to provide people so they can thrive on chaos?* Some of the answer lies in really raising what we think about teamwork—something the military studies very deeply. The team becomes the buffer on which the group defends.

Christopher Dede, Ed.D.
Timothy E. Wirth Professor in Learning Technologies in the Technology, Innovation, and Education Program, Harvard University

leads to better interpersonal skills and decreased anti-social behaviors, and it also improves students' academic achievement. The interactions between social and emotional development and outcome performance make sense. For instance, consider that distractions of any type during learning, including internal anxiety, stress, or personal or professional challenges, can detract from one's ability to acquire and encode new information. However, emotional regulation, resilience, and persistence can improve both learning as well as decision making under stress.[21] Accordingly, emotional regulation skills developed early can improve long-term functioning and can also be improved with time, experience, and formal education. Nonetheless, more inquiry is needed to examine how such capabilities directly impact adult performance and lifelong learning, and importantly, improved developmental metrics and instructional approaches are needed for honing these skills in life.

PHYSICAL DEVELOPMENT

Formal investigation into motor and physical development traces its foundations to the 1920s, when doctors began weighing infants to determine if they met appropriate growth benchmarks.[22] More significant research began in earnest the 1970s and 1980s, spurring significant advancements in the understanding of average motor development, constraints both within and external to a person, and the benefits of aiding, enhancing, and improving motor skills. However, like other developmental domains, much of the research in physical development has been limited to early childhood and disorders, with some unique focus areas for special populations such as sports and military personnel. Yet, beyond the scope of these specific groups, general physical maturation and the impacts of motor skills and practice have been less studied, although that is changing.

Body development, awareness, health, and wellbeing have large impacts on long-term functioning. Increasingly, improved methodologies and new technologies are creating ways to better understand how a body develops into and

As a society or culture, if we think about reimagining learning as a lifelong endeavor, we'll help so many kids. We need to get out of the structure of grades and look at learning as "I've mastered it now, or I haven't *yet*." We need to tailor education.

Michelle Cottrell-Williams
Teacher, Wakefield High School, 2018
Virginia State Teacher of the Year

across adulthood, how physical capabilities can be honed, and how these connect to other developmental domains such as emotional stability, social capabilities, and cognitive development.[23]

Simultaneously, wearable devices and the so-called *quantified self* [24] have created enthusiasm about improving physical activity and the nuances of each individual body. They are providing individuals with the ability to have access to personalized data that was previously unavailable and empowering people to make improved decisions about their health and physical activities as a result.[25] The medical benefits of these technologies have not yet been fully understood at a societal level, nor have they been fully utilized for optimizing human motor capabilities outside of specific, controlled settings, such as Olympic athletic training. However, as the research continues, it's not unreasonable to believe a new theory of physical and motor development that encompasses average, lifelong populations will be forthcoming—one that actively incorporates considerations for human-technology interaction, the processes and impacts of physical development across society, psychophysical literacy, and the interplay of motor development with social, emotional, and cognitive development.

Understanding, philosophically, the holistic connectivity of human capabilities, and how behaviors are enacted across contexts, will be important within

a whole-person development model.[26] A better understanding of the self, to include the physical self, is needed to achieve more holistic, personalized, developmental trajectories.

3. Learning is ubiquitous

Lifelong learning comprises all phases of learning and stages of life, and it occurs across diverse contexts, from school to the workplace, at home and within the community.[27] Lifelong learning activities can happen in formal settings (e.g., courses offered by a university), nonformal contexts outside of fully structured institutions (e.g., meet-up workshops), and in informal and spontaneous ways (e.g., while chatting with a co-worker or reading a post on social media).[28]

Learning already occurs in all of these ways, all the time, and everywhere. To date, however, we've largely documented (and, subsequently, largely valued) only formal learning experiences. Informal and experiential learning can have as much, or even more, impact on individuals' abilities to acquire, assimilate, and apply knowledge. With the development of data science, machine learning, and interoperable data standards that allow us to measure and classify experiences, we're unlocking the ability to better capture and communicate a person's true skill level as well as his or her ability to perform in a variety of settings and across communities. It's irrelevant where a person "learned" something—the transfer of that learning into practice is what matters.

The idea that learning happens everywhere and all the time isn't new. Rather, it's our ability to measure it and communicate about it (e.g., through competency badging and credentialing) that's novel. This also ties to the whole-person principle described in the preceding subsection. That is, various skills contribute to someone's success in the world. In military contexts, for example, there's much talk of grit and resilience, and in higher education, we often reference executive functioning and well-roundedness; however, such capaci-

STACKED CREDENTIALS: For example, in business, a student takes three courses and completes them satisfactorily, and they earn a certificate in the area of finance. After navigating that successfully, they take three courses in marketing and receive another certificate. Then those groups of certificates are stacked into a personalized master's degree. This approach allows the student to acquire credentials in bite-sized chunks and offers more flexibility.

David Munson, Ph.D.
President, Rochester Institute of Technology

ties are rarely measured or reported in transcripts and personnel records. Assessing their applications in real-world contexts and giving "credit" for other lived experiences will also enable our ability to create personalized learning trajectories, improve talent management into the future, and create equitable opportunities for more people.

4. Lifelong learning must employ an asset model

In developmental psychology, an "asset model" refers to an approach that recognizes individuals' unique assets and focuses on adding capabilities to them. This concept is compared to the "deficit model," which focuses on areas of weakness and involves comparing individuals to group averages. The benefits of using an asset model are several-fold. First, there's a psychological benefit in the form of increased energy and the improved outcomes that result when a positive focus is used for learners. This can be seen in sports psychology with relation to performance on the field[29] and is directly translatable to the classroom or boardroom. Building people up to an optimal capability is far more encouraging than forever attempting to "fix" them.

Second, asset models help support whole-person development. Asset models better allow for the inclusion of skills and attributes outside of those measured on averaged, norm-referenced assessments. By looking at these other factors of success, we can better recognize, help develop, and otherwise enable such skills.

Finally, an asset model can better support a focus on continual, lifelong learning. The structure of this type of model naturally defines success at every level, with every addition, and yet has an infinite number of notes, skills, and competencies that one can attain. The reframing of both the learner and the educational system can aid in the reimagination and refocus on how we can improve the system and work toward optimization of each individual, rather than focusing on creating able-workers ready for an industrialized nation.

IMPLEMENTATION

The previous section outlined a vision for lifelong learning in the future. This section outlines specific steps we can take towards that vision.

USE MULTIPLE THEORIES TO INFORM EDUCATIONAL DESIGN. Lifelong learning means learning across time, space, purpose, media, and formality. We'll need to transition this strategic-level concept into tactical-level interventions for classrooms, workshops, training exercises, experiential learning, and other formal and nonformal activities—implementing and integrating theoretical approaches from multiple disciplines, including instructional design, information management, educational psychology.[30]

STACK CONTENT-SPECIFIC, CONTENT-AGNOSTIC, AND SOCIAL AND EMOTIONAL LEARNING. Refocusing education to incorporate a holistic view of human development will necessarily require a shift in educational requirements. However, the ability to add more requirements to an already packed schedule isn't reasonably feasible. Rather, we'll need to change the

organizational structure of formal education and training pipelines as well as take advantage of project-based learning options where multiple skills across the cognitive, emotional, social, and physical domains can be simultaneously developed. Content-agnostic learning strategies, for meta-skills such as self-regulation and executive functioning, will also need to be learned at the same time. A stacking of skills, content, and connectivity across topics should become the norm, rather than the exception, particularly for formal and nonformal education.

MAKE TECHNOLOGY INTEROPERABLE TO MEASURE AND CONNECT. This vision of lifelong learning depends, in part, on the collection and analysis of learner data. To enable that, we'll need to first define measures appropriate for formal, nonformal, and experiential learning. We'll also need to develop the associated technology, including interoperable systems that can safely and ethically aggregate data across time, space, and communities. This "internet for learning" will need to securely store a person's data and make it accessible, across a lifetime, by approved entities who can use those data to personalize learning episodes and developmental trajectories.

USE THE SCIENCE OF LEARNING TO OPTIMIZE THE LIFELONG LEARNING SYSTEM. Learning can be enhanced by employing a set of instructional principles, such as specific teaching and assessment principles. As described in the preceding chapter (Chapter 3), many existing instructional theories already articulate well-documented best practices for supporting evidenced-based teaching and testing. However, we need to widen our perspectives—to consider whole systems, the range of interacting micro- and macro-factors, and their interplay across space, time, and purpose. To accommodate individualized pathways through education programs and other developmental experiences, we'll also need to change how information flows and how people progress through the system. This will impact secondary and postsecondary education, trade training, workforce development, and life experiences. While it's possible to allow technology advancements to drive

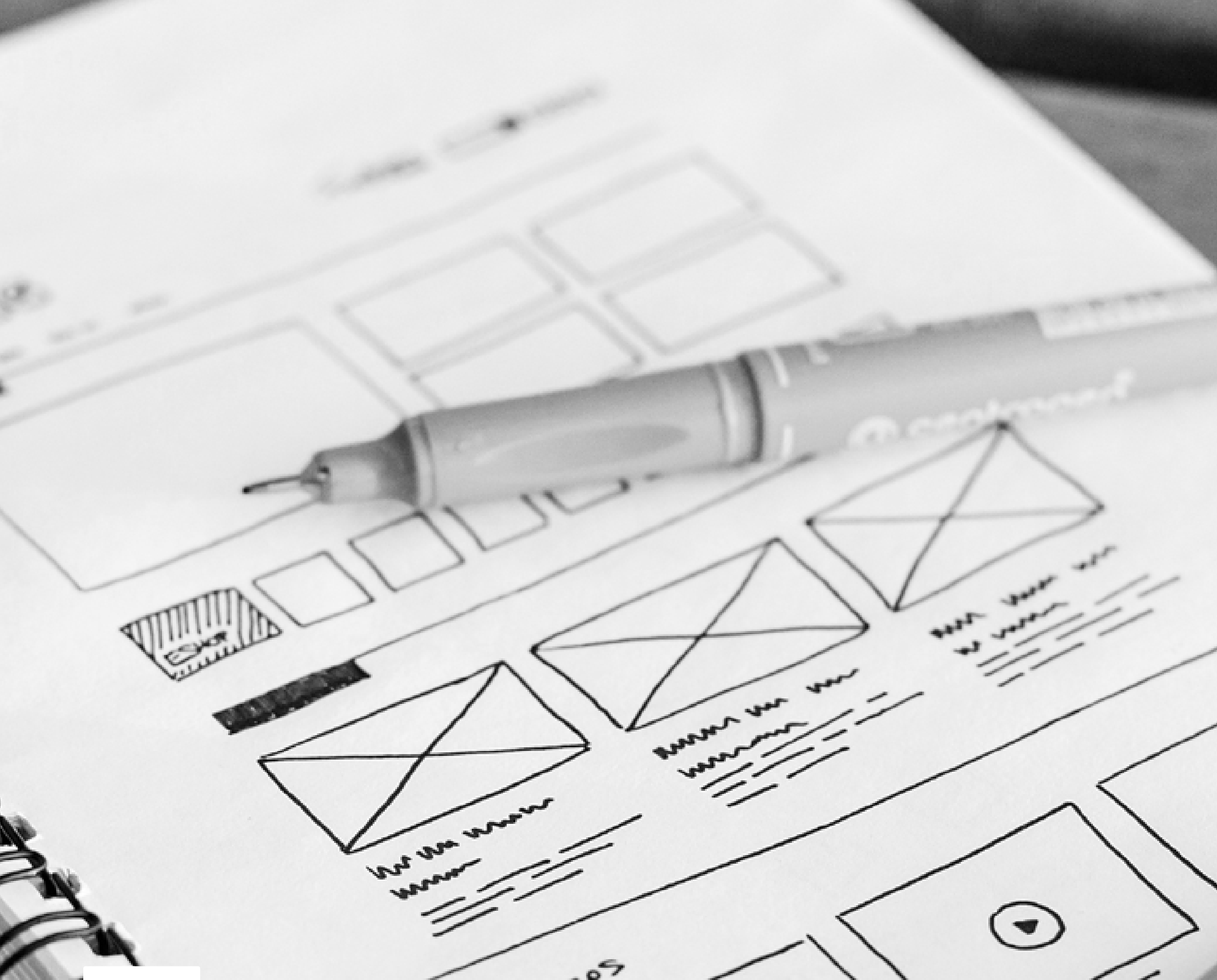
The Department of Defense focus falls short by focusing on eighteen- to nineteen-year-olds and not thinking about how we can support kids at the younger ages. So, by the time we get them in DoD, we're dealing with resilience issues and putting band-aids on problems. We spend 20 years building a new weapon system but our kids in second grade are going to be in DoD in 10 years. The first thing DoD needs to do is consider learning as a continuum to include civilian education. Social emotional learning and executive functioning need to be a focus. There's a whole bunch of things that need to be mitigated before we get them in DoD.

Russ Shilling, Ph.D.

Chief Scientific Officer, American Psychological Association

Former Senior Innovation Fellow, Chan Zuckerberg Initiative; Former Executive Director of STEM, U.S. Department of Education; Former Program Manager, Defense Advanced Research Projects Agency; U.S. Navy Captain (Ret.)

these changes, it would be wiser to help cultivate the ecosystem more holistically. We need to collect evidence and recommend best practices about the elements within it and their collective impact as well as incentivize those elements that bring out its best features—for individuals and society, writ large. Learning science, both its extant research and its inquiry principles, can aid this endeavor, but we must commit to using it for this larger vision.



> Too often, we define the symptoms, not the underlying issue. We tend to problem-solve instead of problem-find. As you try to create these innovative things, you've got to do a really good job separating problem and symptom as you build the ecosystem. The idea of an ecosystem is based on interdependencies, so a technological ecosystem has to work like a biological ecosystem: At the same time, it must take into account all the components—to include the people. These solutions are often developed without the human and user in mind. People don't always think about the end-user when they develop technology.

Jeffrey Borden, Ed.D.

Executive Director, Inter-Connected Education; Chief Academic Officer, Ucroo Digital Campus; Former Chief Innovation Officer, St. Leo College

CHAPTER 5

LEARNING EXPERIENCE DESIGN

Sae Schatz, Ph.D.

The phrase "fog of war" is generally attributed to Prussian military theorist Carl von Clausewitz, who wrote his quintessential treatise, *On War*, in the early 19th century. In it, he describes war as the realm of uncertainty; this gives rise to our classical understanding of the "fog" as a state where information is scant, unreliable, and hidden from view.[1] However, in the modern world of smartphones, broadband, and social media, this concept is taking on a different cast. Today's "fog" isn't caused by a dearth of information but rather by the overwhelming glut of it. The quantity of resources represents only one part of the challenge. So much of the available information is inaccurate, contradictory, inapplicable, or disconnected. There's a signal-to-noise problem. Added to all of this, we're expected to monitor multiple information feeds, carryout parallel multitasking, and pay attention to alerts and interruptions.[2]

Sometimes humorous phrases—infobesity, infoxication, data smog, or info pollution—describe the phenomenon, but its effects are no laughing matter. One result of the pace and abundance of resources is, paradoxically, a drop in productivity. For example, workers need an average of ≈25-minutes to "reset" after being interrupted by a work email, and such distractions account for around one-third of the time a typical knowledge worker spends on the job.[3]

In addition to issues with *efficiency*, information overload can profoundly impact *effectiveness*. Notably, it dangerously affects attention, encoding, and decision-making processes. For instance, when overloaded, individuals are

more likely to monitor the most superficial data and defer to familiar concepts while ignoring conflicting evidence. Attention-deficit disorder specialist Thomas E. Brown has even found that most people, i.e. those without the syndrome, report symptoms similar to it multiple times a day, including the inability to concentrate and to pay attention to what needs to be done.[4] In decision-making contexts, overload depletes mental resources, driving individuals to expedient (rather than optimal) choices, encouraging them to avoid decisions or defer to negative or default options, and allowing unrelated emotions to play an undue role.

We're data rich but increasingly knowledge poor.

Unfortunately, as discussed in the preceding chapter (Chapter 4), creating "more" education and training won't solve this problem. In fact, as we look towards the future learning ecosystem, with its vision of diverse and pervasive lifelong learning, we run the risk that—rather than optimizing our learning and development—we instead add to this destructive cacophony. The learning ecosystem has other potential pitfalls, too; for instance, like today's world wide web learners might be faced with the daunting task of independently curating and synthesizing their own instructional resources. Further, with its reliance on technology, poor usability and breakdowns with other nonfunctional requirements (so called "-ilities") could become insurmountable barriers to its effective and efficient use. In other words, without care, there are an excess of ways that the learning ecosystem could add to the "noise" rather than strengthening and clarifying the "signal."

Solving this problem will require several concomitant solutions. Notably, applying holistic instructional strategies (Chapter 12), developing learners' self-regulation abilities (Chapter 15), and thoughtfully applying automated personalization (Chapter 10) are all essential. In addition, the intentional inte-

> One of the key hurdles in developing students for life is that we're still trying to assess them on information from the past—the way we used to teach. Forty percent of students will work on jobs that don't exist yet. We need to teach them the skills to collaborate and innovate.…If we can google it, then we shouldn't spend our time teaching it! I need to be able to facilitate their learning.

Michelle Cottrell-Williams

Teacher, Wakefield High School
2018 Virginia State Teacher of the Year

gration of these practices, along with the strategic design of learning systems and careful attention to their practical interaction details must be considered. Hence, this chapter focuses on the design of learning experiences as a necessary complement to the other critical elements informing the future learning ecosystem.

LXD: DESIGNING HOLISTIC, LEARNER-CENTERED EXPERIENCES

Broadly defined, *design* refers to a series of interrelated actions, purposefully taken to achieve specific outcomes or goals. People often associate the word with artistic activities, such as painting or fashion; while it fully applies

to these fields, "design" also pertains to any problem-solving discipline that uses a combination of grounded knowledge, skill, and creativity. For instance, teachers may *design* a curriculum for optimal transfer-of-training, and software developers may *design* a new app for security and reliability. Even military leaders discuss operational *design* as a core element of their planning processes.

Learning experience design, abbreviated as LX or LXD, is a relatively new concept, originating around a decade ago.[5] It largely grew out of user experience design:

> The term "user experience" or "UX" wasn't always an overused Silicon Valley buzzword. Coined in the mid '90s by Don Norman, while he was vice president of advanced technology at Apple, it refers to an abstract way to describe the relationship between a product and a human. Back then, Norman argued that technology must evolve to put user needs first—the opposite of how things were done at the time. It wasn't until 2005 that UX gained mainstream relevance: 42 million iPods were sold that year and the mass market experienced great design at scale. … Instructional design is now approaching a similar transition.[6]

With roots in UX, it's unsurprising that educational technologists were among the first to embrace LXD, nor that much of the discussion around it has concentrated on design thinking, usability, and interaction design methods for technology-aided learning. LXD practitioners also frequently emphasize the application of user-centered design, sometimes drawing a distinction with conventional instructional design by contrasting LXD's learner-centered methods.[7] Increasingly, though, LXD proponents are widening its scope beyond (learning) product design, focusing more on broad learning outcomes with an extensive toolkit to apply towards this end. For instance, Margaret Weigel and her colleagues with Six Red Marbles have begun emphasizing LXD's holistic approach to design and its synthesis of instructional design, educational pedagogy, neuroscience, social sciences and UI/UX principles.[8] There's also

growing consideration for informal and social learning, game-based learning methods, neuroscience-informed principles, and the shifting role of teachers from learning providers to learning facilitators. The field, however, still has some maturing to do, and several related disciplines can help inform this.

Industrial Knowledge Design, or InKD (pronounced like "inked") developed around the same time as LXD, and it shares a similar focus:[9]

> InKD…describes an approach involving interrelated techniques drawn from diverse evidence-based scientific disciplines, aesthetic principles, and professional best practices which together help practitioners more effectively and efficiency achieve purposeful knowledge transfer goals and objectives.

Like LXD, InKD considers interaction design and usability principles, and in many practical ways the two concepts overlap. InKD, however, grew out of different foundations and, as such, contributes some unique perspectives. It adds to LXD by identifying a set of (1) foundational scholarly fields to draw upon for theories and concepts as well as (2) practical applied fields from which to derive actionable tools and processes. Specifically, InKD draws from information science fields concerned with the analysis, collection, classification, manipulation, storage, retrieval, movement, dissemination, and protection of information. These include, for instance, instructional design, knowledge management, informatics, semiotics, and media design. It synthesizes these with neurocognitive fields concerned with how individuals interact with data, process information, and form knowledge; these include, for example, learning science, cognitive science, human factors psychology, cognitive ergonomics, and marketing.

The stated goal of InKD practitioners is to use evidence-based techniques to increase individuals' motivation to receive information, its effective conveyance, recipients' encoding and later retrieval of that information, its actionability, and the overall impact of communications. In contrast to LXD, InKD

> But there's this whole other world, conceptually, in different sectors who aren't having conversations with each other. It's shocked me that people really are doing it in silos.
>
> **Emily Musil Church, Ph.D.**
> Executive Director of Global Learning, Prize Development and Execution, XPRIZE

has taken a more academic route, which contributes definitions and conceptual linkages to the burgeoning discipline. This helps ground LXD in established theory and evidence-based practice, and it gives LXD designers a full "rolodex" of disciplines with methodologies and tools ripe for use.

For example, marketing and related disciplines such as consumer behavior, public relations, and advertising offer ample guidance applicable for learning. While that may sound surprising, in practice, marketing and learning professionals share many similar goals: Both try to understand their audiences, generate motivation, capture attention, make their messages memorable, and affect their audiences' downstream behaviors. Of course, marketers generally want to sell products or services, while learning professionals may seek to foster an accurate and robust understanding. Still, the techniques are often the same.

One distinctly applicable approach from marketing is **experience design**. It's a practice usually used in business and entertainment contexts to elevate routine customer "interactions" into more compelling and memorable customer "experiences." Experiential designers are successful when they encourage people to create meaningful emotional and social connections and to construct personal narratives that involve episodic memories and positive associations with the artifacts of that experience (such as a product, in marketing terms).[10]

Experiential design practitioners assert that well-designed experiences convey a more salient "sense" of a product or brand, enhance customer emotions towards it, build loyalty, and ultimately enhance revenue.[11] Applications of it have supported these claims; for instance, a major hospital faced with increasing competition and declining customer-satisfaction used experience design to create a 13% increase in perceived quality of care and a decrease of 33% in customer complaints with no other facility management changes.[12] Other successful use cases, from car rentals to circus entertainment, have also been reported,[13] and we've likely all experienced the effects of well-designed consumer experiences firsthand at theme parks or popular coffee shops.

Philosophically, experiential design isn't too different from classical **experiential learning**. Popularized by David Kolb, experiential learning is "the process whereby knowledge is created through…the combination of grasping and transforming experience."[14] Experiential learning recognizes that not all experiences enrich learning. Instead, meaningful learning occurs when a learner "'touches all the bases'—experiencing, reflecting, thinking, and acting—in a recursive process…"[15]

Experiential learning theory offers a useful model for conceptualizing the processes, and proponents of it have published extensive theories, techniques, and studies about it—some quite useful for LXD.[16] However, like much of traditional instructional design, experiential learning theory generally takes a straightforward approach, focused on cognitive processes with less attention for emotional and social mechanisms, and it tends to treat learners as motivated, self-regulated, and logical actors. This is a place where marketing can usefully augment educational theory. Experiential designers take more holistic approaches, beyond rational cognition or even the immediate experience, and they focus more on practical outcomes. For example, experience design offers a set of tools for selectively manipulating contextual variables to influence experiences and for creating these outcomes at scale. One popular framework involves five categories that designers need to affect, and when all five are

successfully integrated, they form a "holistic experience": [17]

- *Sense* – Reactions to sensory stimuli within or around an experience
- *Feel* – Emotions and their intensity in response to an experience
- *Think* – Mental engagement, e.g., problem-solving or creative thinking
- *Act* – Personal identity and behaviors; a desire to engage or act
- *Relate* – Experiences that provoke a social identity; co-experiences

Experiential designers, and marketers more broadly, tend to more willingly accept the reality that humans aren't rational actors. This gives them more "levers" for affecting outcomes, and it frees them from unfeasible expectations about the logic of consumers' (or learners') thoughts and actions. The study of why and how people make seemingly illogical decisions has grown in popularity over the last 20 years. Today, under the name **behavioral economics**, practitioners have defined a litany of routine decision-making biases, mental heuristics, and cognitive filters that, largely, everyone uses.

Behavioral economics grew out of work by Nobel Prize recipients Herbert A. Simon and Daniel Kahneman (among others), and it's been popularized by Dan Ariely [18] and *Freakonomics* authors, Steve Levitt and Stephen J. Dubner. It also has roots in the **psychology of influence and persuasion**, notably from work by Robert Cialdini.[19]

Behavioral economists Cass Sunstein and Richard Thaler (who also received a Nobel Prize for his work) have expanded the field, widening it to explore ways to "**nudge**" decisions at large scales. Their canonical book, *Nudge*,[20] outlines principles for subtly coaxing people towards better choices. Proponents have used these to great effect. For instance, Collin Payne and colleagues used small cues at a grocery store to increase shoppers' likelihood to buy fresh fruits and vegetables (e.g., designated sections for produce in shopping carts and big green arrows on the floor). These yielded a 102% increase in purchasing for fruits and veggies, with 9 out of 10 shoppers following the green arrows to the produce section when first arriving at the store.[21]

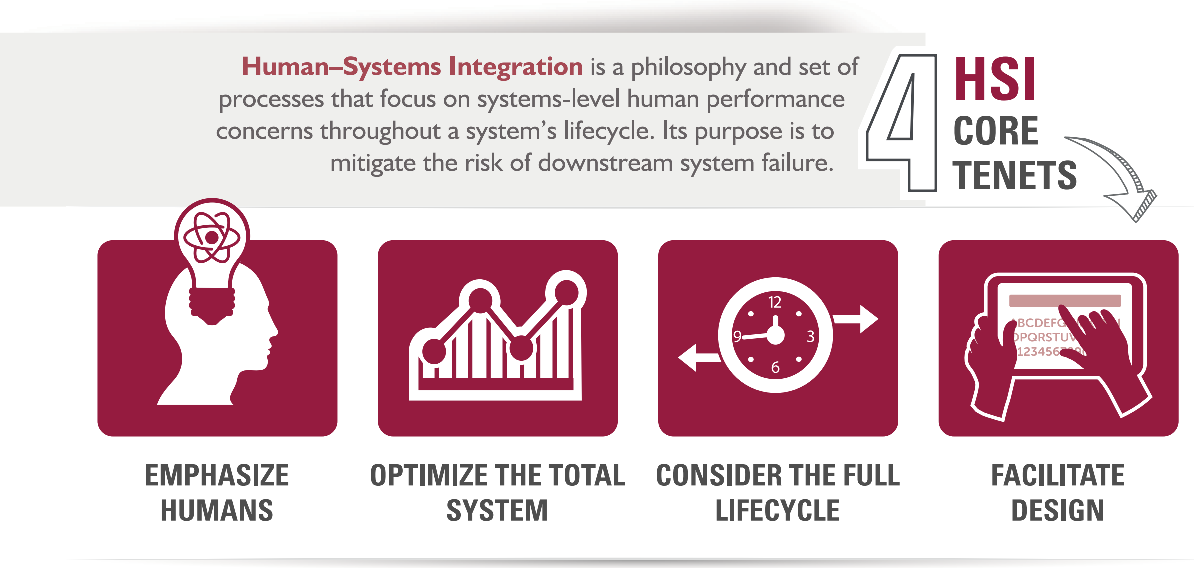
11%

According to polls conducted jointly by Gallup and the Lumina Foundation, **96% of chief academic officers** at higher education institutions felt their programs were **"very" or "somewhat" effective** at preparing students for the world of work—but only **11% of business leaders strongly agreed**. Business leaders said graduates lack the skills and competences their companies actually need.

Source: Preety Sidhu and Valerie J. Calderon (2016). https://news.gallup.com

UX design, experience design, behavioral economics, and nudge all highlight ways in which subtle features and thoughtful design can influence outcomes. But when designing a new system—whether for learning or performance—how do you think through all of the factors potentially affecting behavior? How do you ensure the various elements are designed in harmony and with common ends in mind? **Human–Systems Integration** (HSI) offers some answers here.

HSI is a philosophy and set of processes that focus on systems-level human performance design and development activities. It grew out of the U.S. Department of Defense after a 1981 General Accounting Office report revealed that 50% of all military equipment failures were caused by human error and a corresponding U.S. Army report that found that many military human errors could be traced back to poor development processes that failed to sufficiently consider human performance concerns.[22] Basically, HSI combines systems



engineering methods, human factors principles, and human-centered design practices—yielding a practical toolkit for designers of any system that includes people, technology, and desired organizational outcomes.

HSI has four core tenets:

- **Emphasize Humans** – Emphasize human performance early and often in the system design process; give humans equal treatment to hardware and software
- **Optimize the Total System** – Optimize overall system performance at the comprehensive (big picture) level and not simply at the individual component levels
- **Consider the Full Lifecycle** – Take a long view; maximize a system's benefits—while controlling its costs and mitigating risks—across the entire system lifecycle
- **Facilitate Design** – Facilitate multidisciplinary design; help "translate" among specialists in different disciplines as well as between designers and other stakeholders

Under each tenet, HSI practitioners have developed systematic processes, design tools, and documentation methods. While many of these are designed for projects involving highly complex sociotechnical systems (e.g., building a new aircraft carrier), they can provide LXD designers, at any level, with inspiration and an extensive toolkit to draw from, and HSI's core tenets serve as valuable touchstones for LXD, as well.

Summary

Each of the disciplines discussed in this section can contribute to a maturing understanding of LXD. The foundations of LXD create its underlying philosophy and conceptual paradigm, and its underpinnings in UX offer readymade design thinking principles and user-centered design processes applicable for learning contexts. InKD widens this aperture to more fully integrate information science and neurocognitive science, along with their subfields. In so doing, InKD brings an array of grounded theories and applied tools to LXD.

Commercial fields also offer useful methods. For instance, experience design has concepts, methods, and use-cases for constructing memorable and motivating holistic experiences, often at scale through mass customization techniques. Similarly, behavioral economics helps us understand more about individuals' real-world ("predictably irrational") decisions, and it teaches us ways to "nudge" behaviors, whether to persuade individuals or shift whole communities.

Finally, LXD designers can leverage the four HSI principles as well as its robust collection of established processes and developer tools. Notably, HSI uniquely contributes methods for integrating human-centered design principles with systems engineering, balancing local outcomes against global considerations, and facilitating these designs at scales within production teams and formal organizations.

RECOMMENDATIONS

Each of the fields of study discussed so far offers a wealth of insights for learning design. Below is a list of recommendations drawn from across them, although it surely only scratches the surface.

1. Identify and focus on the actual goal

Across all application areas, a prerequisite of effective design is its conceptualization as a goal-directed process. While this may sound evident, too often people fail to identify the *actual goal*, and instead focus narrowly on immediate actions or process outcomes, without thinking through the larger "why."

Consider, for instance, compliance training—something many of us have endured. Originally, the true goal of a compliance course may have been to address some actual risk, say, to train employees to avoid cyber-scams. The program manager assigned to the job, however, may inadvertently change the goal from reducing cybersecurity incidents to mitigating organizational risk—a seemingly small change. As the job progresses, the goal drifts further, from designing training that mitigates organizational risk to creating an intervention that shifts risk. This, in turn, may influence programmatic decisions; for instance, the program manager might begin to view the mere exposure to training information (rather than effective transfer-of-training) as sufficient for shifting the risk.

Logically, then, the program manager may select the most economical approaches for creating that exposure. Meanwhile, the instructional designer is likely given a stack of materials and told to "train" employees on them—albeit with limited resources. Now, his apparent goal becomes communicating as much information as possible under challenging constraints. Subsequently, supervisors' goals become checking off each employee from a completion list, and employees' goals become completing the training as quickly as pos-

sible.…and so on until, ultimately, everyone's best intentions yield limited actual utility.

UX and user-centered design have proven processes for uncovering strategic goals and designing solutions for them; so, LXD already excels in this area. Jesse James Garrett's *Elements of User Experience*[23] is an oft-cited resource for learning designers, even though his work focuses on digital product design, more generally. His five-layer model starts with *Strategy* (defining goals and user needs), and then progresses through *Scope* (requirements and specifications), *Structure* (interaction models and architectural design), *Skeleton* (interface, navigation, and information designs), and *Surface* (sensory elements and aesthetics) elements.

We did a fairly broad study with 47 large, well-known companies from around the world, and we synthesized the attributes of their learning organizations. In all cases, what we found was that they are mission-focused. They created an architecture clarifying how data-driven decisions about training connect to the mission. Their organizational structures focused on growing internal people and were really helpful to outcomes and buy-in.

Michael Smith
Senior Technical Specialist, ICF

Application of Garrett's methods, or similar goal-focused design processes, can profoundly and positively affect learning design. Using these sorts of approaches means focusing on outcomes rather than processes. They also require that designers (at all levels throughout the processes) challenge assumptions, strive to understand and work towards strategic (rather than just local) goals, and consider creative approaches that fall outside of traditional practices, such as using informal interventions, holistic experience design, or nudge techniques.

2. Apply holistic user-centered design methods

Results published by the National Academies Press show that only 34% of technology development projects in the U.S. are successful, and projects most frequently fail because "(1) an inadequate understanding of the intended users and the context of use, and (2) vague usability requirements, such as 'the system must be intuitive to use.'"[24] As education and training increasingly rely upon technology, it's important to incorporate UX, interaction design, human factors, ergonomics, and other closely related human-centered disciplines into learning design processes.

User-centered design is more than just usability. It needs to consider people holistically. Experience design offers some insights here. For instance, rather than focusing largely on cognition, also consider other internal processes such as emotion, confidence, and motivation. Recently, the Interaction Design Foundation published an article highlighting how LXD, like all other human-centered design applications, is really attempting to solve one (or more) of these five common problems—only one of which directly addresses cognition:[25]

- *Lack of knowledge* – Doesn't understand the material or instructions
- *Lack of skill* – Lacks skill, practice, or ability to apply knowledge
- *Lack of confidence* – Lacks positive, yet realistic, self-perceptions
- *Lack of motivation* – Disinterest in applying cognitive effort or action
- *Lack of resources or tools* – Problems that prevent otherwise knowledgeable, skills, confident, and motivated persons from acting

Again, it's important to consider these dimensions creatively and holistically. As Bror Saxberg, VP for Learning Science at the Chan Zuckerberg Initiative, has pointed out: "Even physical and mental health matter—a very hungry student is unlikely to start, persist, or put in mental effort no matter how gloriously designed a learning experience he's put in. Getting students access to a healthy breakfast is potentially a great personalization of the learning

environment!"[26] In other words, in learning, sometimes more effort needs to be invested in providing resources (beyond those with apparent education or training utility), refining the learning context, or instilling confidence. Think beyond pure information conveyance!

3. Design for real—messy, irrational—humans

Cognitive science and behavioral economics teach that humans are predictably irrational. We're prone to making expedient (rather than optimal) decisions, substantially more motivated to avoid loss than seek gain, and vulnerable to a slew of other biases. Recognize that learners have these "flaws." *That doesn't imply you should deceive or condescend—none of us is a rational actor!* Rather, acknowledge and design for the messiness of humanity. This may mean, for instance, designing for emotional effect or carefully avoiding information overload during a learning experience.

As part of a creative, holistic user-centered design approach, also consider nudge techniques to augment the more obvious learning interventions. Nudges can help individuals overcome inherent biases and might be useful, for example, in encouraging self-regulated learning practices, such as studying or reflection. Also, reach beyond the straightforward cognitive domain, and consider nudges related to other behaviors that may impact learning, like well-being and self-care. Behavioral economics and nudge theory offer excellent examples to inspire these interventions. Related fields, including industrial design, graphic design, and communication, also offer tools for designing interfaces, spaces, contexts, and content elements to achieve persuasive effects.

4. Design holistic experiences

Nothing exists as a simple point in time. As experience design and instructional theory both teach, a given experience is preceded by a preparatory or anticipatory phase, and it's followed by a reflective one. Design for these pre-

> Some experiences are all about people-to-people interaction. There are lots of things that can't be learned online, such as hands-on design projects or working on a start-up company. Sometimes you have to sit with your buddies (fairly intensively, for a few years) or travel overseas. Sometimes you have to be there and you have to immerse yourself.

David Munson, Ph.D.
President, Rochester Institute of Technology

and post-learning phases to the extent possible. Further, an experience has different components. Drawing from experience design, it's useful to intentionally design across the full range of sensory stimuli (*sense*), emotional factors (*feel*), cognitive elements (*think*), personal connections and engagements (*act*), and social identity/co-created elements (*relate*). Also consider the collective effect of integrating these five facets, and think about how to address them before, during, and after a learning experience.

Similarly, don't forget about the power of aesthetics when designing for humans. Psychological research actually shows that "pretty things work better"—that is, individuals' perception of aesthetics directly impacts their performance outcomes.[27] Such aesthetic principles have been well codified for most media by applied creative types; however, practitioners of more "serious" disciplines are often more hesitant to invest in them. In fact, some subcultures, such as certain academic disciplines or military sectors, wholly reject the application of aesthetics (under the assumption, presumably, that too much polish will detract from the "seriousness" of the message—even though scholarly research supports the positive impact of quality aesthetic design).

We're only beginning to understand the psychology of emotional design even though it's been around for decades. Yet, it has formidable promise for LXD.

5. Use systematic processes to design effectively within larger organizations

Increasingly, learning professionals are working in diverse production teams and deploying interventions at larger scales. This marks a shift in the way education and training interventions are developed: Where once they were largely artisan creations crafted independently by experts, they're progressively more likely to be designed and implemented by teams and situated within larger organizations. HSI offers useful tools for navigating the practical challenges that come with these changes.

A first lesson from HSI is to consider a long view of a system attempting to maximize its benefits, while controlling costs and mitigating risks, across its entire lifecycle; that is, through its initial design and development phases, along with its implementation, operation, and eventual retirement stages. The point is, when designing a new process, system, or learning experience, consider it within the context of the organization across time: How will it be designed and eventually built? How will it be rolled-out to stakeholders? How will it be maintained and continuously improved over time? When should it be retired?

HSI similarly offers methods for conceptualizing organizational components. Typically, HSI practitioners recognize the manpower, personnel, training, safety and occupational health, human factors engineering, habitability, and survivability domains. They try to take these factors into account when created integrated designs. For instance, if enough operators (manpower) aren't available, then they might increase the experience requirements of operators (personnel) so that each can perform more efficiently. While these classical domains have some applicability for learning systems design, LXD practi-

tioners will likely need to modify this model. What's more important than its specifics, however, is the broad, system-wide perspective it encourages. When designing a learning experience, it's useful to not only consider its delivery but also, for instance, how many learning professionals are needed to implement it (manpower), what skills those professionals need (personnel), how they'll be preparation for their roles (training), and the context in which they'll deliver the intervention (habitability).

Finally, HSI practitioners often facilitate a multidisciplinary design process, helping to document and "translate" between specialists in different disciplines (e.g., between sociologists and computer scientists) and negotiate requirements among interested parties (e.g., brokering compromises between training specialists and manpower analysts). In practice, this means that HSI practitioners spend considerable time eliciting inputs from various stakeholders, documenting assumptions, clarifying friction points, and developing "shared representations" that transform these requirements and analyses into meaningful, unambiguous formats such as storyboards, concept maps, process diagrams, storyboards, and wireframes. These HSI processes and tools are useful for LXD designers, as well.

6. Maximize global outcomes vs. local processes

Explicit in the "learning ecosystem" concept are the notions of diversity and interconnectivity—across an entire lifetime (or, at least, career). This connectivity creates new opportunities for us to consider learning experiences in concert rather than as isolated events. Other chapters in this book discuss instructional strategies for connecting learning events (Chapters 4 and 12, in particular). This chapter, however, adds practical considerations that LXD is uniquely positioned to address.

First, consider the impact of lower-level decisions in aggregate. What's the *gestalt*, or combined impression, they collectively produce? Do certain implicit

"

> The challenge is getting teachers to share the imperfect; they like to reach perfection, and convincing them to share an imperfect product is difficult. The historical Vermont paradigm has been teachers are artisans working in relative isolation, but that system is breaking down. It's antiquated and not working relative to personalizing student learning. We need to scale and showcase the very good work that's going on in some of our districts—but not all.
>
> **Daniel French**
>
> Secretary of Education, Vermont Agency of Education

messages, such as emotional or motivational suggestions, carryover from one event to the next? For instance, imagine a multipart workshop taught by four different instructors. If each asks trainees to complete some kind of pretest, engage in initial icebreaker activities, and respond to post-training questions, the trainees are likely to grow bored, lose motivation, and might even become cognitively overloaded. A clever designer might find ways to tie the different segments together, introduce novelty throughout the four segments, build-in time for cognitive reset, and find ways to simplify the overall UX. Similar considerations apply as we scale-up our reference frames and begin integrating more diverse learning experiences across time, subject, and media.

Second, when designing learning interventions, it's tempting to try to optimize each individual event, without considering their collective, long-term result. For example, consider a company that's decided to shift from traditional, weeks-long vocational courses to on-the-job, just-in-time training. On the one hand, this method helps avoid inefficient massed learning where individuals often wastefully forget much of what they learned. On the other, it risks creating disjoint learning that individuals struggle to meaningfully integrate and comprehend beyond a superficial level. It may also create unforeseen burdens on more experienced operators in the job environment. There is nothing

inherently wrong with just-in-time learning; rather, the point is to consider system-wide learning strategies that balance holistic efficiency and longitudinal performance against local optimizations. If each module, course, or individual designer develops local optimums in isolation, we risk creating overall inefficiencies and ineffectiveness. Strategy—informed by learning science—must be applied to, and integrated across, all levels.

7. Continue to synthesize theories and practices from diverse disciplines

LXD, like the future learning ecosystem concept writ large, represents a synthesis of varied and emerging disciplines. Learning design teams in the future will likely involve instructional designers, learning scientists, learning engineers, technologists, data scientists, and other professionals. LXD fills a unique void, helping to integrate the diverse perspectives across these team members, giving voice to learners' (and other stakeholders') needs, and encouraging the use of disciplined human-centered design practices.

It's impossible for any one person to thoroughly know all of the disciplines that inform LXD, but it's important for LXD designers to avoid "reinventing the wheel" with their work. As this chapter has shown, many existing domains offer useful theories, processes, use-cases, and tools. Seek out these prior solutions; curate and remix them for your own purposes. Look in creative places, such as the advertising literature or systems engineering manuals, and look to conventional principles of instructional design, learning science, and cognitive psychology, too. This discussion on LXD isn't meant to supplant those important fields but rather to supplement them by integrating design principles that consider human-system interactions, applied cognition, organizational dynamics, and user experiences. Together, in synthesis, these various methods can help learning designers to not only create quality instruction but to better achieve learning outcomes for real people, in real-world contexts.

Everyone comes through the same education system, and we get locked into believing that's the way we learn—when we really don't.

Doug Tharp
Senior Learning Project Manger
Nuclear Regulatory Commission

Technology

Interoperability allows data to easily flow, even among applications developed for different purposes, using a standardized vocabulary, structure, and cadence. Interoperability implies common standards that promote system-to-system communications, potentially across organizational boundaries and institutional firewalls, using specified data formats and communication protocols. These standards form the fundamental building blocks for technology-enabled lifelong learning by establishing consistent protocols that can be universally understood and adopted by related systems to enable data exchange about learners, activities, and experiences.

CHAPTER 6

INTEROPERABILITY

Brent Smith and Prasad Ram, Ph.D.

Interoperability, when applied to learning, transcends the full spectrum of learning environments, systems, data, and organizational entities that individuals encounter throughout their lives. The highly mobile nature of our population requires that information about learning be shared in an efficient manner across this ecosystem of learning. When individuals advance in their careers, or transfer from one career to another, or simply progress through the continuum of learning from one organization to another, high quality data about their learning experiences needs to be shared. However, today's learning ecology consists of stovepiped organizations using highly customized management systems, accessing disparate sources of data in any number of nonuniform architectures. To achieve the future learning ecosystem concept, we'll need to exchange data across a full range of products, made by different vendors, and encountered throughout the entire continuum of lifelong learning. Key to managing all of this data is interoperability—afforded through the use of internationally accepted technical specifications and standards.

In today's digital world, information is readily accessible anywhere and everywhere. Large-scale social networks, interactive content, and ubiquitous mobile access are emerging as driving technologies in education and training. At the same time, data science presents new opportunities for assessing the effectiveness of learning content for different learners, understanding organizational trends across large volumes of learning data, and using amassed data to continually improve training and education. Yet, there are interoperability challenges. Today's digital learning ecosystem is fragmented. Data from one

system can't always integrate with data from another, which means learning records aren't easily transferable between institutional systems and across organizations. Training and education institutions don't even record the same learner activities or capture learner achievement information in the same formats, which further complicates our ability to aggregate data.

FORMAL LEARNING PROGRESSION

Beginning with K–12 education, most state educational systems use products from multiple vendors, and each district deploys their systems independently. Historically, these applications have used limited (or no) underlying data standards. Instead, most employ their own internal data models, and integration across systems requires a patchwork of connections at the state and/or local levels.[1] Consequently, there are gaps in the integration among disparate applications, and many systems are simply not interoperable. Ideally, data from multiple products, such as learning management systems, student information systems, and learning object repositories, would be aligned to the same common data standards, enabling seamless coordination across these applications.[2]

The existing higher education system is also its own stovepipe. With its focus on credit hours, semester-long courses, and formal credentialing, these institutions often fail to account for new practices available in a digital, and globally connected, world—such as emerging global online learning environments that increasingly blur formal and informal practices. Students are now much more interested in interactive and self-guided approaches, and with so much information online (and often available for free), universities are no longer the only places to find higher-level learning. Consequently, the value

> The biggest problem we have is the lack of **connected infrastructure** across postsecondary learning systems.
>
> **Amber Garrison Duncan, Ph.D.**
> Strategy Director, Lumina Foundation

of a degree is gradually decreasing as employers place greater weight on a candidate's capabilities developed outside formal education.

Within military education and training there are many different schools and training programs designed to foster technical, professional, and leadership skills in service members. Many of these programs, their instructional technologies and personnel information systems, exist in stovepipes. Further, historically there's been a separation between the education and training communities across the U.S. Defense Department. Education traditionally occurs incrementally and involves grappling with ambiguity while thinking and reflecting about the concepts being learned.[3] Training is linked to readiness and offers opportunities to apply knowledge, skills, and abilities in a manner that provides immediate feedback and progress measurement.[4] Within the current context, training and education have different reporting structures, motivations, and logistical requirements such as fuel, personnel, and the access to the appropriate environments or equipment. Combined, this leads to data being acquired from many different sources but with little-to-none of it standardized or connected.

Types of Interoperability

Rapid technological change has become the norm in the modern landscape of training and education. Within learning contexts, the pressure of such changes is felt acutely by educators, trainers, administrators, and learners alike. Table 6-1 shows a different view of the various learning technologies, environments, organizations, and outcomes a given learner might encounter throughout his or her career. This matrix highlights the numerous types of interoperability required to facilitate a future learning economy. This is largely due to the organizational design of the current learning landscape as well as the different reporting structures and responsibilities for when and where training and education occur.

Some Representative Examples of Where and How Learning Occurs

Learning Technologies	**Learning Environments**	**Learning Organizations**	**Learning Outputs**
Electronic Classrooms Interactive e-Books Learning Mgmt. Systems MOOCs Mobile Devices AR and VR Systems Live, Virtual, and Constructive Simulations Embedded Training and Performance Support IoT systems Wearables Performance Qualification Systems	Instructor-Led Classrooms Live Training Ranges At Home and Cafés In Transit on the Train or Bus On-the-Job Experiences and Mentorship Field Trips and Military Staff Rides Workshops and Conference Libraries Navy Ships Afloat Austere Job Sites and Military Stations Simulation Centers	K–12 School Districts Trade Schools Colleges and Universities Postsecondary Accreditation Agencies Licensing and Credentialing Bodies Corporate Human Resources Programs Military Manpower, Personnel, Training, and Education Systems Industry Associations International Organizations and NGOs	Transcripts Diplomas and Degrees Standardized Test Scores (SAT, ACT, ASVAB) Licenses and Certifications Digital Badges and Micro-Credentials Formal Performance Evaluations Resume Listings Continuing Education Units and Professional Development Units School and Workplace Credits

Table 6-1: Learning Activity Matrix

Many types of interoperability are required:

- **Systems Interoperability** – Digital systems need to work together. The existing systems we use to collect, manage, analyze, and report on data are often disconnected and don't always work well together. Some of the technology challenges center around data standards, including inconsistency of standards and the inability to access data in a usable format. Progress is being made by numerous ongoing efforts across government, industry, and academia.
- **Application Interoperability** – Systems are comprised of numerous disconnected applications that, theoretically, must all be capable of communicating about how they're impacting learning for each individual. Currently, different applications track performance differently, and the ability to infer information about each activity within an application is not always well-defined.
- **Data Interoperability** – The seamless, secure, and controlled exchange of data between applications is critical to maximizing our ability to understand individuals' learning. Not only are data are often stored in isolated data within applications, but these datasets often use custom or proprietary data models. Common data standards, along with supporting data governance and metadata information, are needed to maximize return on investment in interoperable applications, perform workforce planning, and support other derived benefits from data analytics.
- **Human-Machine Interoperability** – The different environments where learning takes place impact the types of learning technologies used. As new tools and technologies come into play, individuals must become more technically savvy and industry must find ways to better support the seamless transition of learning across a multitude of computing platforms, devices, and learning modalities.

- **Organizational Interoperability** – Data ownership is a critical obstacle that impedes true interoperability. In the knowledge economy, data is often monetized and leveraged for purposes other than learning. Organizations as well as savvy individuals are reluctant to share their data. Creating cross-platform and interorganizational interoperability will require a change in culture, and, arguably, that poses an even more difficult challenge than technical interoperability.

Already, educational institutions, training organizations, and instructional technologies collect some learner data, such as, demographics, assessment results, teacher observations, learner-created content, attendance, and course grades. However, these data points don't provide a complete picture of a learner unless connected with data collected throughout the continuum of learning. Additionally, we're touched by learning broadly throughout our daily lives by numerous informal interactions, both with other people and through our own self-directed efforts, but none of those data are captured in a manner that allows aggregation, comparison, or analyses.

Resolving these interoperability challenges is key to setting the foundations of a global learning economy that enables learners to constantly update, retool, rethink, and relearn.

VISION

Common standards and shared technical specifications create the underpinnings needed for the future learning ecosystem, from a technology interoperability perspective. These standards consist of published documents that establish key interface specifications, communication protocols, and data structures designed to facilitate interoperability among connected components. In this context, interoperability specifications form the fundamental building blocks

for lifelong learning by establishing consistent protocols that can be universally understood and adopted by any component of the learning ecosystem to enable data exchange about learners, activities, and experiences.

> The more people understand Google and the benefits of cross-domain work, the more they want it—and the more the silo boxes are a problem.
>
> **Jeanne Kitchens**
>
> Chair of the Technical Advisory Committee for Credential Engine; Associate Director of the Center for Workforce Development, Southern Illinois University

In the future, such interoperability will unlock rich data about learners and learning activities, empowering organizations to build comprehensive solutions that meet the needs of their specific populations. Standardized, documented interfaces will also enable "plug-and-play" replacement of new or upgraded capabilities on existing platforms. In other words, interoperability will allow organizations to add, modify, replace, remove, and support different learning technologies (from different vendors) throughout their lifecycles.

Interoperability will facilitate data aggregation across the continuum of learning. Analyses of these data, in turn, will enable learners to optimize their learning journeys across their many diverse learning activities, throughout their careers, and, ultimately, across their lives. These data could also help address institutional questions, such as determining which academic courses produce the best learning outcomes or predicting workforce skill gaps. Combined with the science of human capital management, enterprise learning analytics could also help organizations address their strategic talent management goals, including succession planning, career assessments and growth, development, retention, and knowledge sharing.

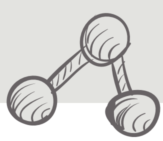
Several types of technical interoperability are needed to achieve this vision. These include standard ways of defining competencies (for use in both learning and performance contexts), for encoding data about individuals' performance and behaviors, for aggregating and visualizing these performance data in meaningful ways, and for describing and locating various learning activities. The following subsections describe each of these in more detail.

Competencies

Interoperable frameworks that form the "common currency" of the future learning ecosystem

Competencies form the interoperability crossroads of the future learning ecosystem, serving as the Rosetta Stone between different learning systems and workforce applications. A competency describes a set of skills, knowledge, abilities, attributes, experiences, personality traits, and motivators needed to perform a particular task. Competencies might include technical, business, leadership, social, ethical, or emotional capacities, or any number of other personal traits and capabilities. Additionally, competencies may be highly dependent on their usage context; differences in environmental factors, task complexity, and related processes or policies can all impact their applications.

> Organizational competencies need to be encapsulated within a **competency framework** to map all learning activities a learner might encounter within an organization.



A competency model (also called a competency framework) combines multiple competencies, and their underlying factors, into a framework related to particular domain, career, or job area. Some competency models further separate this information into levels of mastery, such as information about the level of competence required at different occupational levels,

and these various elements within a competency framework can have many nonexclusive relationships with one another.

Education and training organizations may use these frameworks to inform learning outcomes, and they're also widely used in business for defining and assessing requirements for both hard and soft skills associated with job performance. The use of common competency frameworks will allow data from different sources to be meaningfully interpreted in and translated to other contexts.

One challenge is that there's no standard for competencies. Different industries, accreditation authorities, and trade associations use a variety of different existing frameworks. Some follow any number of specifications and others do not. Many competency frameworks include rubrics, performance levels, or other data that can be used to evaluate proficiency while others rely on supplementary, external components to house assessment and evaluation criteria. Some competencies are linked to the environment in which the competency is expressed, and others are motivated by training or education objectives (e.g., knowledge, skills, abilities). To enable the future learning ecosystem vision, shared vocabularies, classifications, and frameworks of competencies will be needed, and these will need to allow for commonality and reuse of competency objects and their descriptors across diverse organizations. Shared metadata vocabularies might also be required, to include descriptors such as the type of skills included (e.g., psychomotor or cognitive skills), skill decay estimates, or relevant environmental factors that impact or inform the description of a competency.

Activity Tracking

Data about learners' performance and behaviors

Activity streams are a nearly ubiquitous feature on many of the applications we use on a daily basis. For example, newsfeeds on social media use activity streams to record users' interactions. Activity streams use serialized data that consist of statements about behaviors. Such statements typically involve

The American Council for Education has developed a digital competency-based credential that will enable an individual to transfer learning from work to a degree path. The T3 Innovation Network* is testing the use of competency translation algorithms to review curricula and competencies. The algorithms are reviewed by faculty to confirm and are at an 80% accuracy rate right now—and that will continue to improve. The ability to use advanced technology will help us start to harmonize towards a more common competency language since we, as humans, cannot connect the 1000+ frameworks that exist without technology's help.

Amber Garrison Duncan, Ph.D., Strategy Director, Lumina Foundation

*The T3 Innovation Network is an initiative of the U.S. Chamber of Commerce Foundation for exploring emerging technologies and standards in the talent marketplace to better align student, workforce, and credentialing data.

a subject (the person doing the activity), a verb (what the person is doing), and a direct object (what the activity is being done to or with); optionally, other elements that describe the performance context can also be incorporated. The resulting dataset tells the story of a person performing an activity. Examples include "Mike posted a photo to his album" or "Emily shared a video." In most cases, these components will be explicit, but they may also be implied.

Within the future learning ecosystem, activity streams need to capture what individuals do, which learning activities they perform, and how they perform. Each entry in the stream should be timestamped, meaning that a learner can have progress measured as a function of time, not simply a function of state. The goal of activity streams is to provide data (and metadata) about activities in rich, human-friendly formats that are also machine-processable and extensible. This interaction data will need to be published by any activity a learner engages with. In some instances, data might be generated by a learner's performance, and, in other cases, a system might generate data based on system events or key milestones achieved by a learner. Alternatively, data may be

generated to establish the context of the learner, the application, or other components within the learning ecosystem.

The subject of an activity is nearly always the learner but could, foreseeably, be an instructor, cohort, or other human or machine agent. The direct object of an activity depends on its context, as do the verbs (although to a lesser extent). Universal terms, particularly verbs, will need to use a common vocabulary across systems, otherwise the data will lack semantic interoperability and lose much of its utility. By formalizing a common vocabulary, activities can reference an established set of attributes along with rules for how the dataset is stored and retrieved by components in the learning ecosystem.

Universal Learner Profiles

A common place to aggregate and visualize learners' data

The current way learner records are managed is insufficient for the evolving needs of instructors, learners, and organizations. Today, a transcript is typically used to record learners' permanent academic records. Transcripts usually list the courses taken, grades received, honors achieved, and degrees conferred from a formal academic institution. Only this most basic of information follows individuals across their different learning episodes. Teachers and trainers have little visibility into individuals' past performance, such as what other instructors have noted about them, the informal or nonformal learning they've experienced, or their strengths, weaknesses, and individual needs.

In the future, transcripts—or "learner profiles"—will still need to expand to incorporate a broader range of credentials, micro-credentials, and other learning activity information along today's formal learning information. They will also need to become more dynamic, shifting away from being static records and instead acting as dynamic tools that learners and organizations can use to determine learners' unique paths to achieving proficiency in all their desired competencies.

Society expects us to be innovative.

It's imperative that we evolve because changes are happening whether we lead them or not. The demands society places on innovation mean that we've got to stop looking through the lens of today and start looking through the lens of tomorrow with a vision for K-12. Our kids today will be the workers, leaders, academics, or soldiers of tomorrow.

So, the questions to ask are: How can we use technology to help us pedagogically? Can we conduct formative rather than just summative assessments of individual aspects of learning that ultimately enable us to give learners a better education than they've ever had?

Our academic standards are now in a machine-readable format and we can do true gap analyses to make inferences to inform teachers' decisions and also save untold billions of dollars. Information rich micro-credentials, such as badges, support measurable progression, process, and evidence of learning. Using xAPI that records these steps builds a documentation of learning that lives beyond the institutional level. It supports lifelong talent-management and allows our systems to be seamlessly aligned across time and communities. We need to ensure that the same measurement we use is both useful today and understandable to the next community.

Learning is truly measurable.

Keith Osburn, Ed.D.

Associate Superintendent
Georgia Virtual Learning
Georgia Department of Education

> …it's more about the person, not the technology.
>
> **Emily Musil Church, Ph.D.**
> Executive Director of Global Learning, Prize Development and Execution, XPRIZE

Learner profiles have the potential to empower personalized learning within the future learning ecosystem through better data that can inform learning in new and meaningful ways. As envisioned, a learner profile is analogous to a mashup of information about a learner, populated from various sources and consisting of both explicit and derived data. A future learner profile might include a broad range of information, such as demographic data, data about a person's interests and preferences, and existing competencies and those that need to be developed (in the personal, academic, and career arenas). It also might include information someone's learning strengths, needs, and the types of learning interventions that have been successful in the past. We use the term "universal" when describing the learner profile, because we envision data from multiple systems flowing into a shared representation. Further, as a learner's interests change, or as he or she becomes competent in new areas, the profile would continually update to reflect the latest "state" across time.

Safeguarding learner data to preserve privacy is an important legal and ethical consideration. We could also imagine that individuals would need to control their own data; so, we anticipated that individuals would have access to obtain, share, and interact with these artifacts as well as to control the other people, organizations, or applications that can access them.

Activity Registry

Arrays of diverse learning activities

An activity registry is an approach to capturing, connecting, and sharing data about available learning resources. Unlike federated repositories, search en-

We have 11 missions in the Coast Guard and every one of them is diverse, with different stakeholders for each. Our borders, to include our waterways, are very important, and if we were to go to war, we'd be supporting the Navy. So it's important that we're connecting and maintaining readiness; yet, we're bounded by many different DHS and DoD policies. It's critical that we can be disruptive thinkers about training, and it's even more critical that we can interoperate.

Gladys Brignoni, Ph.D.

Deputy Commander, Force Readiness Command and the U.S. Coast Guard's Chief Learning Office

gines, or portals, activity registries are a Resource Distribution Network with open APIs that anyone can use to register, expose, or consume learning resources and information about how those resources are used. Key features include the ability to generate and manage content metadata (data about the publisher, location, content area, standards alignment, ratings, reviews, and more), manage taxonomies and ontologies, manage the alignment of content with competencies, generate and manage paradata (data about the metadata, such as resource usage, comments, rankings, and ratings), perform semantic search services, and create machine-actionable metadata for AI-based recommenders.

An activity registry houses metadata, paradata, assertions, analytical data, identities, and reputations that flow through the distribution network. An activity registry will also contain access information and permissions for different learners. The activity registry requires a trusted relationship with different learning-related activities as well as other essential services, such as launch and discovery. We imagine that any of the communities or organizations that consume a learning resources will also capture information about how those resources are used, such as their context, user feedback, user ranking, rating, and annotations, and

these paradata might be incorporated into the activity registries. We imagine that such usage data and third-party analytical data could become valuable for resource discovery and for understanding what learning resources are most effective.

Learning Content Metadata

Data that describe learning resources

To effectively enable activity registries, the resources they point to will need to be described in some manner. Such descriptions are encoded as metadata. In training and education, many different metadata formats have already been explored, including Learning Object Metadata (LOM; IEEE 1484.1.1), which is commonly used with SCORM managed content, the Dublin Core Metadata Initiative, and the Learning Resource Metadata Initiative (LRMI).[5]

LMRI is a particularly common metadata framework, used for describing learning resources in web-based instruction. LRMI was adopted by Schema.org[6] in April 2013, which allows anyone who publishes or curates educational content to use LRMI markup to provide rich, education-specific metadata about their resources with the confidence that this metadata will be recognized by major search engines. Founded by Google, Microsoft, Yahoo, and Yandex, Schema.org's vocabularies are developed by an open community process with a mission to create, maintain, and promote schemas for structured data on the internet, including on web pages, in email messages, and beyond. LRMI's adoption into Schema.org provides many benefits. In theory, nearly any Schema.org "*thing*" could be defined as a learning resource. Therefore, LRMI addresses those metadata properties that distinguish content when it's deliberately used for learning. This was done by adding learning-resource properties to key root types. For example, LMRI incorporates the *CreativeWork* property, which includes descriptors such as *Educational Use*, *Educational Alignment*, and *Course*,[7] the latter of which is defined as a sequence of

one or more educational events and/or other types of *CreativeWork* that aims to build knowledge, competence or ability of learners.

Talent Management

Bridging education, training, and workforce silos

The preceding subsections highlighted the interoperability afforded by technical standards. We've primarily discussed these standards within the context of training and education, but they also apply to workforce activities. The worlds of human resources, training, and education have never been more closely linked. Organizations, employees, departments, data, customers, and partners can no longer function successfully in their own silos. As mentioned above, today's training and education systems are often disconnected from one another; further, they're rarely interoperable with internal or external HR systems. This results in incomplete or duplicative data, inefficient or inaccurate reporting, complex and costly vendor management, and inefficient and manual HR transactional processing.[8] Standards and specifications that allow these disparate systems to communicate have the potential to assist organizations of all sizes to improve performance and workforce satisfaction.

The systems around talent management need to work seamlessly. Within the future learning ecosystem, an employees' digital records will include data from various stages of their careers related to recruitment, training and development, and performance management. Many new standards are actively being developed through the International Standards Organization (ISO) relevant to business-crucial areas such as compliance and ethics, workforce costs, diversity, leadership, occupational health and safety, organizational culture, productivity, recruitment, mobility and turnover, skills and capabilities, succession planning, and workforce availability. All these areas contain specific metrics and reporting recommendations. Creating systems that combine these workforce data with other training and education information will enable the

advancement of evidence-based human capital management policies and provide access to lifecycle data for transaction processing. It will also provide the data needed for workforce planning and strategic decision making.

Talent, too often, is treated as an afterthought. With increasing retirements and a fluid workforce, organizations are finding it more difficult to manage the end-to-end employee data lifecycle due to duplicative HR IT systems across agencies that are unable to interface and exchange data. The different systems in use today are like different countries—with distinct languages, customs, and religions. They use diverse data formats and moving data between them is difficult and, when done, is often accomplished in nonstandard ways. To improve the interoperability of HR systems, the different applications need a common record that covers all aspects of the employee lifecycle, from hire to retire, for each person. Additionally, to achieve greater synergy within an organization and to drive human capital performance across the breadth and width of organizational competencies, organizations must shift from ad-hoc to strategic talent management programs.

These enhancements to workforce HR systems will benefit learning institutions, as well. Experts commonly agree that most learning takes place on the job.[9] Hands-on experience allows individuals to refine their job skills, make decisions, address challenges, and interact with others in the organization. They also learn from their mistakes and receive feedback on their performance, and they may engage in coaching, mentoring, collaborative learning, and other forms of social learning. Rarely (if ever) are these informal learning experiences tracked. By understanding how and when these types of learning take place, we can construct more robust profiles of individuals, whether to inform their learning journeys or to increases the collective intelligence of their organizations.

The capacity of an organization to innovate, change, and become more effective depends on employees' capabilities, thus highlighting the importance of developing those individuals.[10] However, just as we need better indicators

for undergraduate performance, we need better measures of performance in the workplace. The competitive nature of the global economy and the world stage increase the need to focus on the human capital supply chain that organizations employ. While this concept is attractive to organizations, there are ongoing challenges for its implementation. Workforce planning requires authoritative data for proper modeling and predictive analytics. Recruitment requires integration with onboarding and performance data to improve hiring strategies. By enabling a common language that the different systems can read from and write to, we're able to identify hidden dependencies and relationships within an organization and provide other analytics that help them make better and faster data-driven decisions.

In America, companies are struggling to close a skills gap, which is negatively impacting their ability to compete and grow in a global economy. The U.S. Chamber of Commerce Foundation's Talent Pipeline Management initiative is exploring how employers can close the skills gap by improving how they communicate or "signal" their hiring requirements. Through this work, they're creating the Job Data Exchange that enables a set of open data resources, algorithms, and reference applications for employers and HR technology partners to use to improve how competency-based hiring requirements are defined, validated, and communicated. This provides a critical linkage between the job performance data, credentialing systems, and learning record systems.[11]

IMPLEMENTATION STRATEGIES

The future learning ecosystem promotes an increasingly complex world of interconnected information systems and devices. The promise of these new applications stems from their ability to create, collect, transmit, process, and archive information on a massive scale. However, the vast increase in the quantity of personal information being collected and retained, combined with

our increased ability to analyze it and combine it with other information, create valid concerns about managing these volumes of data responsibly. There is an urgent need to strengthen the underlying systems, component products, and services that make learning data meaningful. The following subsections outline a foundation for an enterprise-wide learning ecosystem that can adapt and grow with the needs of the organization.

1. Identify and describe organizational competencies

Organizations need to inventory the skills required to successfully perform all business functions within their institutions. These include technical, professional, and leadership capabilities across numerous departments, divisions, or lines of business. Each role within the organization will typically include a career trajectory with an accompanying learning trajectory for the knowledge, skills, attitudes, and other contributing factors an employee needs to do their job effectively. Different roles may share the same competency but have different contexts for how that competency is performed or a weighting for how much it impacts a particular job. A competency framework provides the common reference model across HR, training, and education systems, and the critical indicators associated with competencies within it help quantity individuals' performance. As new tools, technologies, and processes transition into the work environment, competency models will need to be continually updated effectively operate in the future.

2. Formulate a data strategy

The current landscape of disparate learning and personnel systems will continue to evolve for the foreseeable future. A cohesive data strategy needs to be implemented to help identify all of the relevant data types required to support the human capital supply chain, to define the relevance of different data types over time, to identify an approach for capturing the decay of importance be-

tween different data types, and to identify authoritative sources for generating each data type. An effective data labeling strategy will enable automation, increased analytics, and an associated lifecycle for how long the different data elements remain relevant. Data labeling attaches meaning to the different types of data, correlated to the different systems that generate the data across the lifelong learning continuum. This allows all systems in the learning ecosystem to use the data as needed, such as to adaptively tailor learning to individuals. Patterns of data should also be explored to derive additional insights at institutional levels. Consider both structured and unstructured data that may be generated in different areas, and develop clustering strategies for how to organize the different data types so that all components have access to the data they need.

3. Define standards, specifications, and vocabularies

The more we can formalize the requirements for standards, specifications, and shared vocabularies used across the nation, the easier it will be to integrate components into the ecosystem. While there are many automated technologies that can semantically align different terms, there are benefits to designing systems that use shared vocabularies to describe learning activities, digital content, learners, and competencies. Activity tracking across learning activities also works best when each activity uses a common library of terms for different instructional modalities, media types, or as a roll-up to other systems in the organization (e.g., talent management).

4. Define the governance strategy

Organizations need to be responsive and proactive in recruiting, educating, and preparing their existing workforce for the future. The knowledge and skills required to be successful today will change and new tools, technologies, and methodologies will migrate their way into the organization. Emphasis

As we think about creating an interoperable system across DoD, my initial thoughts are just how big the problem is. With four different Services, how is it that you generate buy-in from each—who for a long time have been doing their own thing? I think the first question is: What are the digestible parts that would have commonality across the Services? If you can determine that, then how do you get buy-in to the digestible parts? Because in the end we all want to know how we're going to do it better, faster, cheaper; this is a problem of all the Services.

Thomas Baptiste

Lieutenant General, U.S. Air Force (Ret.)
President and CEO, the National Center for Simulation

should be placed on the protection of personally identifiable information, protected intellectual property, and other proprietary organizational data. As new systems come online, all aspects of the data strategy, competency framework, and human capital supply chain will need to be revised. Workforce planning strategies should tie into the lifecycle management of these critical components. Governance should also be addressed in the data strategy so that specific indicators and outcomes can be tracked, measured, and analyzed.

These four steps provide a strategic framework from which a learning ecosystem can be built. These aren't trivial tasks and will be implemented differently in each organization, depending on its size, complexity, and goals. Collectively, these steps allow organizations to embrace the future learning ecosystem concept and to benefit from the rich data it will produce, allowing businesses to maximize their workforces and learning-delivery organizations to optimize and manage the quality of training and education experiences they offer.

> In thinking about risks associated with the learner data needed to power personalized adaptive learning, privacy and security are clearly at the top of my mind. But we need to expand the set of values beyond those two in determining if the use of student data is responsible/ethical. There's value in advancing knowledge, ensuring students are successful, and promoting the development of practices that have the potential to affect a lot of people. This multi-faceted approach isn't new: A lot of these values are considered in the context of human-subjects research reviews. It's important for the academic community to have a similar process for considering such a range of values in evaluating our practice, in addition to our research.

Martin Kurzweil, J.D.

Director, Educational Transformation Program, Ithaka S+R

CHAPTER 7

DATA SECURITY

J.M. Pelletier, Ph.D.

Data breaches, like traffic accidents, are inevitable. Yet, it's also a requirement that we progress as a nation to a digitized learner ecosystem. Accordingly, this chapter describes the ways we can be proactive in simultaneously managing the likelihood of occurrence, damages of impact, and potential for contagion of breaches across learner data systems. An effective learning architecture requires security to preserve privacy, to prevent cheating by the individual, and to prevent intrusion by external threat actors. Accordingly, balanced effort is required across the three pillars of security: confidentiality, integrity, and accessibility. While most security investigations focus on confidentiality and integrity, the access to that data enables timely and well-informed decisions. Further, users are highly likely to invalidate security controls if accessibility is inadequate. All of these concerns can be addressed by hardening devices and networks in a way that places users at the center of each improvement. To do this efficiently, data security design should enable individuals and organizations to limit the spread of breaches within current and future learning architectures. Thus, this chapter describes principles and strategies that will allow distributed learning environments to keep pace with developments in cybersecurity.

Data Security Threats and Challenges

Several issues must be addressed as we progress to a nation that embraces the accumulation of data. We must recognize both those elements that protect the human as well as the need to protect the system and integrity of the

> You can't hold firewalls and intrusion detection systems accountable. You can only hold people accountable.
>
> Daryl White
> Chief Information Officer, Department of Interior
> …as quoted in the *Information Security Management Handbook, Sixth Edition, V7*

data. In America, an individual's privacy is a fundamental right, and security preserves the dignity that privacy allows. Yet a subset of learners will struggle with integrity; learners cheat by bypassing access controls to steal answers or alter grades. Also, foreign adversaries constantly use cyber means in their attempt to assess national capabilities and influence organizational priorities. Finally, regardless of resource investment, we're seeing consistent increases in both the impact and probability of breaches.

AMATEUR THREATS

The most immediate concern is that malicious software is becoming increasingly automated. Learners need little technical ability to steal answers and change grades. There are many thousands of free, step-by-step tutorials that walk would-be attackers through the process of conducting the most-known technical penetration.[1]

FOREIGN THREATS

A broader challenge exists in relation to foreign adversaries. As advanced persistent threats become increasingly capable, the former cornerstones of security are quickly becoming obsolete. This is especially true as our nation races to keep pace with adversarial advances in quantum and classical supercomputing capabilities.[2] Any widespread use of data management systems should be resilient to known attack methods and provably secure against cryptographic brute force, side channel, and intercept attacks.

SOCIAL ENGINEERING

The value of access to an organization's learning architecture shouldn't be underestimated. Expert-level social engineering results in manipulation of the behavior of entire societies. There's a broad and deep body of knowledge in the use of deception and propaganda to control populations. This happens on an individual level through confidence artistry and is scalable to any number of persons using similar techniques. Centuries of Russian military thought and government experimentation in social engineering provide us with the domain of маскировка (*mask-ee-rove-ka*), which roughly translates to "masquerade," "disguise," or "deception," and includes the concept of reflective control. Reflective control is the art of strategic injections of (usually truthful) information to cause a person or society to choose freely actions that are most beneficial to the other party. The select injection of truth can manipulate perception. Further, a single, well-designed falsehood within a trusted environment has disproportionate network effects. Just as a person can be manipulated to act on behalf of another person's interest, so too can organizations. At a societal level, this shapes political will and, ultimately, public policy.

INVESTMENT MODELS

Recent research in information security economics has attempted to build models that help evaluate optimal levels of information security investment. These generally apply risk management strategies to calculate an optimization function associated with expected monetary loss, assessed vulnerability, and likelihood of a breach. Some of these models consider breach contagion effects, but they aren't prescriptive in suggesting how the economically optimal funding amounts should be invested.[3]

There seems to be consensus among economists and cybersecurity experts that the only solution is to spend more money on any sort of solution that can lock down the data. That way of thinking about security is analogous to allocating enormous resources to make every car into a tank!

SUMMARY OF CURRENT BEST PRACTICES

Subsequently, cyberspace has become an asymmetric battlefield, upon which attackers operate at a disproportionate cost advantage and seek to win through attrition. While these problems may seem intractable, there are specific best practices that can preserve the confidentiality, integrity, and accessibility of distributed learning architectures without exorbitant expense. The single most critical practice for security requires regular examination of standards, requirements, protocols, and implementations. Effective cybersecurity requires extensive review of technology specifics, which is far beyond the scope of this document. Instead of an exhaustive review, we consider here a few extant vulnerabilities within the current distributed learning protocols. The goal is two-fold: first, to support immediate improvement and, second, to support ongoing sustainment in security that will result in cost-efficient reliability across distributed learning architectures. The implementation plan at the conclusion of this chapter recommends a process for further review and hands-on validation, which will allow a rank-ordered task list after a structured risk management process.

Future Learning Ecosystem Implementation Layers

Data security is a mature, albeit continuously evolving, field relative to the general IT field. Those best practices translate to the distributed learning architectures, which build upon common operating systems, servers, and network technologies. However, the future learning ecosystem will also need unique interoperability data formats, transport layers, interfaces, and storage solutions. Two examples of these are xAPI and Kafka.

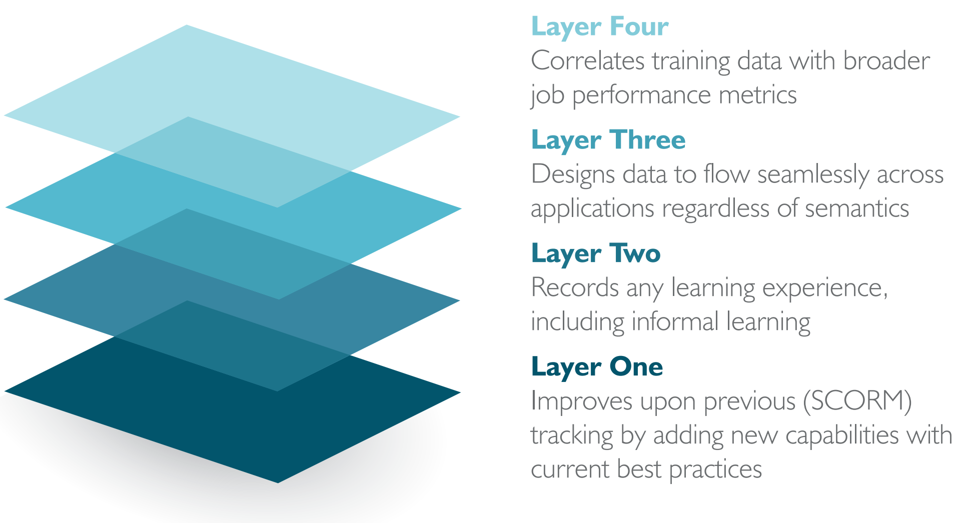
EXPERIENCE APPLICATION PROGRAMMING INTERFACE

xAPI is an example of an interoperability specification that enables data collection about a wide range of online and offline learning experiences. It provides a standardized data structure and vocabulary for data captured across a variety of learning technologies. xAPI is designed for simplicity and flexibility, and it provides a basis for communicating and evaluating learning throughout the future learning ecosystem. A non-exhaustive list of application areas include: real-world activities, experiential learning, social learning, simulations, mobile learning, virtual worlds, and serious games.

Systems conformant to the xAPI specification record interaction data, such as between people and learning content. These interactions can occur anywhere and often signal the potential for learning. The recording process involves the transmission of statements to a Learning Record Store (LRS), which is part of the xAPI technical specification. Each LRS can then share the recorded xAPI statements with other LRSs and across a range of other learning technologies (as access controls permit).

The xAPI specification provides this interoperability through a series of implementation layers:[4]

xAPI Interoperability Implementation



Security within and across each of these layers must allow for consistently reliable application without exposing organizations to unnecessary information risk. This is especially important as data become increasingly standardized across the wide range of learning interactions tracked by xAPI. Any security evaluation starts with an assessment of each of the controls that are currently in place. A preliminary analysis reveals that there are several vulnerabilities that require immediate consideration.

KAFKA

Apache Kafka is an example of a message-oriented middleware system that can process learning record changes at a massive scale. It was developed as the message collection and analysis mechanism at LinkedIn and is probably best-known for allowing data processing with very high volumes of variable message rates in real-time.[5] Its features include partitioning, replication, and fault-tolerance, which make it ideal for distributed messaging of big data. Generally, it is a unified platform that allows for reliable and asynchronous message exchange.

ACCESS IS KEY. Our biggest issue right now in readiness: How do we get training to the point of need? Access is really the thing we have to focus on. Our networks are very secure, but they're very slow and performance is lackluster. And then we have BYOD (bring your own device), but not all Marines have tablets and computers though they all have phones. So the real question is: "What is the balance between access and security?" I feel like I'm always fighting against the network guys—how do we get both yeses? Is the mission goal *security* or *learning*?

Larry Smith
Technical Director
U.S. Marine Corps College of Distance Education and Training

Other examples of message-based middleware that can work for learning processing are based on the Advanced Message Queuing Protocol 1.0, which is an international standard (ISO/IEC 19464) with several implementation options that are optimized for smaller systems. Some of these options include ActiveMQ, Apache Qpid, and RabbitMQ.[6]

VISION FOR DATA SECURITY IN THE FUTURE LEARNING ECOSYSTEM

As standards and best practices change, so should the implementations within the distributed learning architecture. This suggests the need for a theoretical orientation that allows for a practical, continuous evaluation of learner data security.

Nothing humans make is impregnable, yet data sharing is also unavoidable. In the realm of distributed learning, this means we should acknowledge that we can neither completely eliminate the risk of a student hacking a data stream to get examination answers, nor entirely prevent sophisticated attacks from taking or changing information. However, we must find ways to (a) reduce the likelihood of successful attacks and (b) develop barriers to reduce their impact if penetration occurs. The core tenet of normal accident theory is that technological failures are inevitable when a system is complex, tightly coupled, and has catastrophic potential.[7]

Thus, we must consider the potential issues that can result from failures within interdependencies among complex systems involving identification, access control, authorization, auditing, network segmentation and boundary enforce-

ment, endpoint protections, encryption, and transaction security. The assumptions of normal accident include:

- Humans cause errors;
- Small accidents tend to escalate into big ones; and
- The organization of technology—not technology itself—usually causes problems.[8]

The most common application of accident theory is on roadways, where we assume there is no set of systems that will entirely prevent all traffic accidents. Subsequently, safety mechanisms like seat belts and bumpers limit the impact of each accident, and medians and shoulders on high-speed corridors provide spacing that prevent the tragedy of fatal collisions from becoming multi-car catastrophes.

Current research in normal accident theory and organizational reliability suggests we should design strategies that handle breaches as inevitable and aim to prevent their spread.[9] Despite our best efforts, systems within every distributed learning architecture have been, or eventually will become, compromised; so, our goal is to minimize that impact. In practical terms for distributed learning, it's recommended to maintain segregation of data lakes through network and organizational segmentation. Each department or agency should maintain separate content networks and, within them, build compartmented sections for each learner type. This will simultaneously control the spread of breaches and preserve data integrity by creating a content blockchain. Further, centrally-managed syndication and subscription to content will help preserve confidentiality to avoid aggregation that can reveal organizational priorities and strategic aims. A few specific security concerns are addressed in the remainder of this section to ensure network and endpoint protections, in the near term, and security sustainability, in the long run.

Hardening Networks

The highly technical nature of a firm's information storage and retrieval system makes the Intrusion Detection System (IDS) and Intrusion Prevention System (IPS) useful components for breach identification. While most intrusion detection and intrusion prevention systems monitor network traffic, host-based anomaly detection can reveal and report unauthorized attempts to access examination answers or to manipulate grades. There are also several commercially available Security Incident and Event Management tools (SIEM), which explicitly monitor network logs and data flows for indicators of compromise. The inclusion of these tools is likely to significantly increase awareness of security compromises, reduce detection timelines, and inform organizational needs for response. For distributed learning, data streams should be designed as one-way valves. Data lakes should be tightly patrolled with a SIEM and organizational Security Operations Centers (SOC), which monitor the SIEM data and conduct live response around the clock. Several Managed Security Services Providers (MSSPs) provide SOC capabilities for organizations that are too small to maintain their own defenses.

CROSS-LEVELING STATE-OF-THE-ART SECURITY

A more extensive review of the xAPI and Kafka standards, in light of the Kerberos protocol, is likely to yield an elegant alternative to the current security schema. Furthermore, the integration of a robust security layer within the API can provide abstraction that simplifies the instantiation of authentication mechanisms across content providers and distributed learning hosts.

Kerberos was developed as the network authentication protocol for on-campus communications at Massachusetts Institute of Technology. Its main strength is that it's designed to be secure even when performed over an insecure network. More specifically, passwords never transit the network during the session authentication process. Each transmission is encrypted using a secret key

EXAMPLE – PRELIMINARY VULNERABILITY ANALYSIS

The most significant residual risks associated with Kerberos occurs when endpoints are compromised. If the Authentication Server is compromised, attackers can generate a validly encrypted Ticket Granting Ticket. If the Ticket Granting Server is compromised, attackers can configure it to ignore the initial authentication to the domain controller, as well as obviate the service prescription. That allows the attacker to generate tickets for any service, not just those that would be normally defined by the Authentication Server, but it cannot authenticate new users to the domain or allow offline password cracking. If the Service Server is compromised, there is no fraudulent ticket generation, but it can bypass the need for client to have a ticket at all.

Note: The Golden Ticket Attack grants tickets and persistent access to any service for 10 years, but can be prevented with a relatively simple network security setting.

and attackers can't gain unauthorized access to a service without compromising an encryption key or breaking the underlying encryption algorithm. It's designed to protect against replay attacks, where an attacker eavesdrops and retransmits legitimate communications. Further, the protocol uses symmetric key encryption, which makes it computationally efficient at the device-level, and thereby suitable for use on resource-constrained devices. The use of symmetric key encryption also provides resilience to potential compromises of the Certificate Authority within a Public Key Infrastructure. Finally, Kerberos has a widely-available open-source implementation, which facilitates non-proprietary integration into government-owned systems.[10]

HARDENING DEVICES

The best way to harden a device is to take an offensive mindset to determine the ways an attacker might attempt to compromise that system. Through attack/defend exercises, defenders can learn which vulnerabilities result in the most critical exploits and investigate ways to remedy security deficiencies. Regular penetration tests will reveal vulnerabilities on each device and across

networks. Across any distributed learning architecture, this is most important for those devices related to the access control for a personalized learning data store network (public key repositories, domain controllers, certificate authorities, and authentication servers) and for evaluation materials (content repositories that include answer keys).

SOCIAL HARDENING: DEVELOPING RESILIENCY

Learning management is integral to the concept of social hardening. To economize network and device hardening efforts, an explicit evaluation of human behaviors within the organization along with associated training interventions are needed. From a security perspective, social hardening is an opportunity to develop organizational resiliency because humans start to learn the "why" behind the design of technical controls and how they can prevent and contain

EXAMPLE – SOCIAL HARDENING ACTIVITY

Purple team exercises are one mechanism for social hardening. They teach network defenders what attacks look like on their own network. These testing and training events involve live attack/defend scenarios for IT staff and a cross section of their managerial hierarchy. A team of penetration testers (red team) openly engage in attacks while the threat-hunting defenders (blue team) try to spot and deny those attacks in real-time. These scenarios can take place on the organization's environment, in a virtual replica of that environment, or within a simulated disaster scenario on a near-neighbor environment. Purple team scenarios can also involve sets of novice and expert end-users, who are valuable for considering and evaluating impacts, based on their experience. The incorporation of end-users can provide insight to how, when, and why users may attempt to bypass security controls. In practice, these exercises reduce the time it takes to detect attacks, test organizational response procedures, discover previously hidden vulnerabilities, and ultimately result in a superior organizational security posture. Purple teaming exercises often work best when performed by internal staff and facilitated by an independent third-party. When necessary, external penetration testing can be a strong substitute, if internal red teams are unavailable.

data breaches. The most important component of social hardening, though, is institutional retention that creates a culture of best practices.

Implementation Recommendations

Broadly speaking, the plan for implementing security within the future learning ecosystem should include four phases. Some form of this plan is likely the most rapid and cost-effective way to improve cybersecurity capabilities in an extensible and forward-leaning manner.

PHASE 1: DEFINE SECURITY REQUIREMENTS. The need for security is evident, but which standards to mandate is less clear. Security requirements engineering is a first step in this process because it offers a disciplined look at the interoperability needs across the system-of-systems. This step will identify and stress-test the various security procedures already in place, validate which portions of those protections are inadequate, and conduct collaborative attack/defend exercises with current content providers to validate findings.

EXAMPLE – IMPLEMENTATION ACTIVITIES

Phase 1 is likely to include a series of purple team exercises. These involve a team of penetration testers (red team) who openly engage in attacks, while the threat-hunting defenders (blue team) try to spot and deny those attacks in real-time. These scenarios create local, contextualized learning because they generally take place on the organization's actual environment or in a virtual replica of that environment.

During Phase 2, the process of local learning that occurred during Phase 1's purple team exercises should be transformed into multimodal instructional content. This should involve building the notes and findings from Phase 1 into case studies that educate the wider community. For example, these might include lectures, online labs, and evaluation materials specifically designed to teach learning technologists about the threats and cybersecurity protocols of their own organizations.

This will culminate in an economized application of available resources focused on prioritizing efforts to those most likely, critical, and impactful security improvements.

PHASE 2: DESIGN, IMPLEMENT, AND EVALUATE SECURITY LEARNING ACTIVITIES. Learning new processes is an optimal way to project continuous improvement into the future. During the execution of Phase 1 there's an ability to monitor and evaluate the practices of security requirements engineering. These evaluations can yield individual and organizational learning activities that are derived from use cases within actual distributed learning architectures. Further, integrating Phase 1 and 2 schedules and teams is highly likely to generate cost-efficiency. These learning activities will build understanding regarding the specific processes for security engineering within distributed learning environments, which is highly likely to yield future security improvement across multiple generations of the technology itself.

PHASE 3: DRAFT SECURITY POLICIES AND STANDARDS. In addition to mandating specific security protocols and acceptable technologies in the short-term, there's an opportunity to inculcate a long-term process focus within security policies and standards. For example, requiring a third party to conduct an annual security vulnerability assessment is common to the military (e.g., Army FM 3-19.30.2) and has been adopted within the financial industry (e.g., 23 NYCRR 500). An organization's draft security policies and standards should help integrate both product- and process-focused needs into an attempt at establishing lasting security across its learning ecosystem.

- **Networks** – Network hardening should be the first step in securing learner data. This can take several forms, though it could involve an initial round of vulnerability testing, development, and deployment of a Kerberos-inspired alternative relevant for the learning ecosystem data formats, repositories, and transportation layers (such as defined by the xAPI and Kafka standards). This is especially promising given the

potential for applying normal-accident theory to achieve a high-reliability learner data schema that hardens both network and, later, devices.

- **Devices** – Device hardening is likely to present challenges due to the disparate nature of machines seeking to read, write, and execute the files associated with learner data. Subsequently, this step consists of systematic review of individual agency standards, and will recommend a viable minimum standard for device connectivity.
- **Humans** – Social hardening is a difficult challenge, especially for technology-focused personnel. Evaluating and improving the human component in data security requires an understanding of both human behavior and technology to define policies and standards that shape behaviors that deny human-enabled cyber-attack vectors. Careful review of existing personnel security standards, such as the Army's Threat Awareness and Reporting Program (AR 381-12), are likely to yield a series of best practices for securing the human element in distributed learning architectures.

PHASE 4: PREPARE EXPECTATIONS AND MANAGE RISK. No security plan can completely eliminate risk. The accelerated pace of technological change makes this especially true for systems that aggregate, store, and process data. The final phase of this plan explicitly examines the risks, controls, and residual risks associated with current security findings in light of expected future technologies. The result of Phase 4 should include an assessment of when the policies and standards drafted in Phase 3 may require update. Major deliverables should include a list of assumptions, findings, and indicators/warning of disruptive impact on the analyses conducted in this plan.

Security is like planning —
indispensable as a process but
quickly irrelevant as a product!

CHAPTER 8

LEARNER PRIVACY

Bart P. Knijnenburg, Ph.D. and Elaine M. Raybourn, Ph.D.[1]

Privacy is particularly important for distributed learning systems because managing learners' trust among disparate sources is like managing the privacy of apps on one's phone—a difficult task that arguably becomes even more pertinent when it deals with sensitive learning data. Particularly, some systems explicitly consider every activity of their users as a potential learning activity, thereby playing into people's tendencies to learn and train not just in the classroom but also in natural settings.

Modern digital learning systems employ ubiquitous data collection to enable highly personalized and pervasive learning recommendations. Going beyond a fixed, one-size-fits-all curriculum of activities, these systems track learners' progress in minute detail and tailor subsequent learning activities to their performance. While this helps tremendously in achieving highly efficient learning practices, the data collection and user modeling practices employed by such systems may cause privacy threats that act as a barrier to their adoption. As users' trust in personalization providers is starting to fail, it's crucial to investigate the privacy implications of such data collection and learner modeling practices.

Social networking capabilities, often featured in learning systems, may also introduce privacy considerations that may inhibit their adoption. Users have expressed severe privacy concerns with social networks, yet users of these applications tend to struggle with managing their privacy on these networks. Hence, it's important to provide thoughtfully designed privacy management mechanisms in learning applications.

PRIVACY IN THE FUTURE LEARNING ECOSYSTEM

In many existing learning systems, privacy controls are an afterthought—a series of privacy settings accompanied by a complicated privacy policy. In contrast, the future learning ecosystem should employ the philosophy of privacy by design[2] to allow developers and researchers of such systems to select the characteristics that best alleviate users' concerns. Moreover, the implementation of user-tailored privacy will allow systems to model learners' privacy concerns and provide them with adaptive privacy decision support.[3]

While this may nominally lengthen the development cycle, it prevents a situation where the system has numerous complex privacy settings and a complicated privacy policy that learners are unable to navigate—or worse yet: no privacy protections at all.

Data Collection

Many types of data might be available through a digital learning system, including learner runtime activity, competencies, and context. Such data can be collected anonymously or identifiably connected to a learner's profile. The data collection practices of a digital learning application can have unique privacy implications depending on the type of data collected, its source, and its potential identifiability. This section discusses how to consider those aspects when defining and developing the data collection practices of a digital learning application.

☆ the ecosystem must incorporate privacy into its design and development as early as possible

PRIVACY DECISION-MAKING

Arguably the most important advice for developers of distributed learning systems is to study the privacy concerns and practices of the (potential) users of those systems. One of the most consistent findings in privacy research is that people vary extensively in their information disclosure practices.[4] Generally, users of digital systems acknowledge the benefit of data collection for personalization, but when taken too far, the same data collection can deter users from using the system extensively or even dissuade them from using the system at all.[5] The point where this happens differs per user. Understanding how different learners make privacy-related decisions can inform strategies that help alleviate these issues.

An often-used conceptualization of people's conscious information disclosure decisions is the "privacy calculus," which suggests people make privacy decisions by balancing the perceived risks and perceived benefits of the available choice options. Therefore, it's important that digital learning systems highlight the relevance of a requested disclosure behavior, and that they refrain from asking for information in situations where relevance is not readily apparent.

Research has also demonstrated that user trust has a significant influence on disclosure behavior in digital systems.[6] Therefore, building trust is an important strategy for increasing acceptance of the data collection and tracking practices employed by modern digital learning systems. Trust can be built by ensuring learning applications originate from trustworthy sources, and by employing sensible, transparent data collection practices from the outset.

However, people aren't always rational in their privacy decision-making: when they make "heuristic" privacy decisions, they don't carefully weigh risks and benefits; instead, they rely on superficial but easily accessible cues, such as website reputation, ostensible privacy guarantees, and design quality. Digital learning systems should survey their users to learn more about the heuristic decision processes that may negatively affect disclosure. Moreover,

they should tailor to learners' heuristic privacy decision-marking processes by giving them sensible default settings and providing both rational (e.g., privacy policy) and heuristic (e.g., privacy certifications or seals) sources of trust. Learners with low levels of motivation (privacy concerns) and/or low self-efficacy (privacy literacy) are more likely to make heuristic privacy decisions. If rational privacy decision-making is required, digital learning systems can attempt to instill motivation and ability in their users by providing contextualized privacy controls and easy-to-understand privacy information, such as instructions designed as cartoons or comic strips.[7]

COMMUNICATION STYLE

Privacy in digital learning systems extends beyond personalization; it's also relevant to the interpersonal ("social networking") aspects of these systems. Social networks typically provide a plethora of mechanisms to manage one's privacy beyond disclosure, and research finds that users tend to employ a wide variety of strategies to limit their disclosure, such as the six privacy management strategies uncovered by Pamela Wisniewski and her colleagues[8] (see Figure 8-1). These archetypes arguably extend to other social network-based systems, including social learning platforms and other applications or features that leverage social networks in learning systems.

Internet users also choose their social network based on their preferred communication style. Research[9] suggests services that broadcast implicit social signals (e.g., location-sharing social networks) are predominantly used by "FYI (For Your Information) Communicators," who prefer to keep in touch with others through posting and reading status updates. They tend to benefit from the implicit social interaction mechanisms provided by broadcast-based social network systems. People who are not FYI Communicators, on the other hand, would rather call others, or otherwise interact with them in a more direct manner. They tend to benefit more from systems that promote more direct interaction. In order to tailor to both types of communicators, digital learning

systems should employ both automatic social-network style sharing (for FYI Communicators) and direct, chat-style interaction (for non-FYI Communicators). Further, since the communication styles of FYI and non-FYI Communicators are at odds, developers should also pay attention to effects of integrating different communication styles within a single application.

Digital learning systems that employ or implement social network components should tailor their privacy functionality to different privacy management styles

LEVELS OF IDENTIFIABILITY

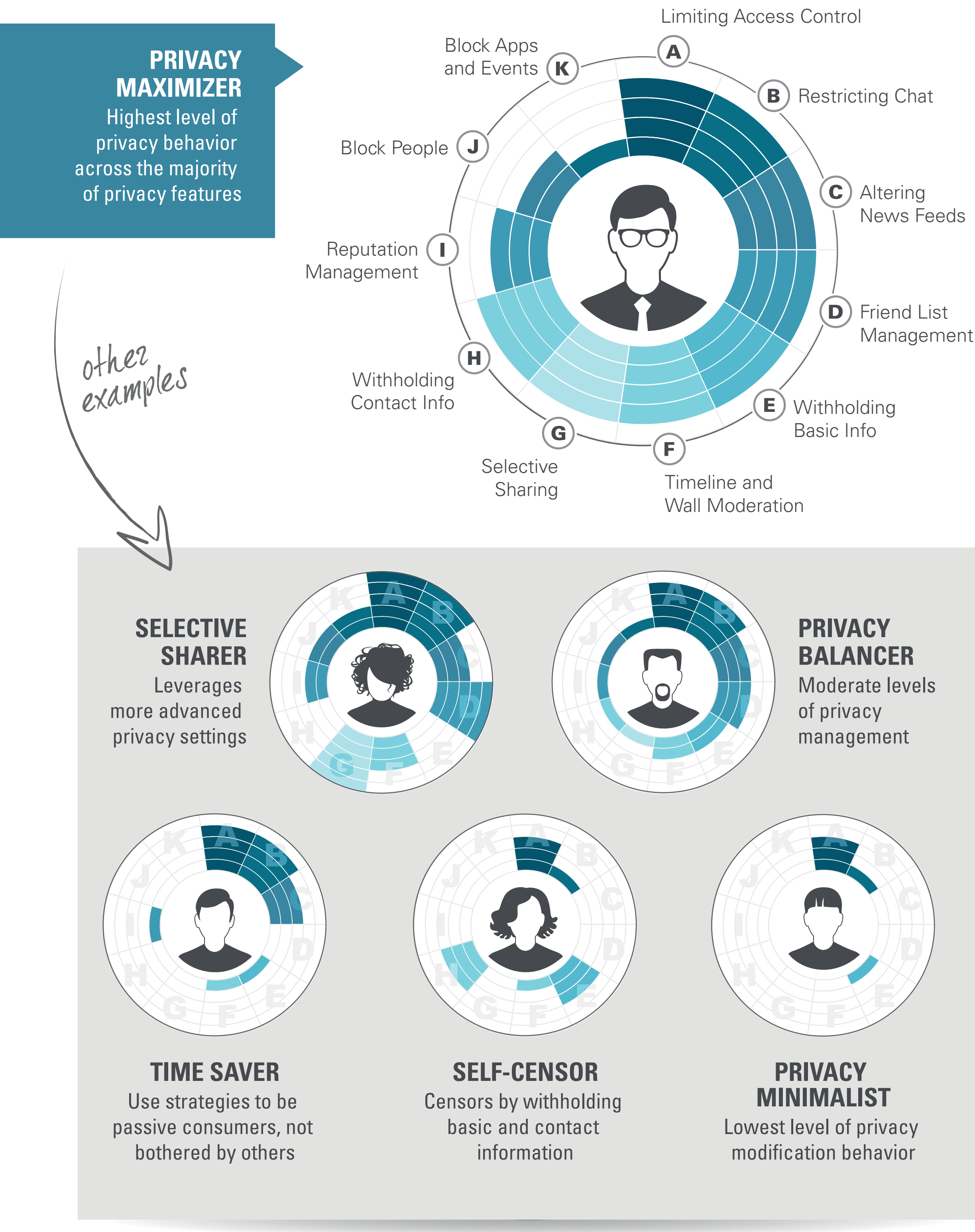
The use and sharing of learners' personally identifiable information (PII) deserves special attention, because it presents the risk of revealing the identity of learners to other parties. PII can be defined as any information that could be used on its own or with a combination of other details to identify, contact or locate a person, or to identify a person in context. The privacy concerns associated with PII can be mitigated by allowing users of a digital learning system to remain fully anonymous.

Fully anonymous interaction means that there are no persistent identifiers associated with the user. This is difficult to accomplish in digital learning systems, though, since most learning activities follow a trajectory over multiple interactions, which means that the system must be able to recognize the learner across these interactions. More realistically, users can be allowed to interact with the digital learning system under a pseudonym. The effectiveness of pseudonyms and other means of de-identifying personal data has been called into question, however, since such data may still be at risk of being re-identified, especially in digital learning systems that collect data with high dimensionality and sparsity.[10] Regardless, researchers have argued that

Figure 8-1 (derived from work by Wisniewski and colleagues)

Privacy Management Archetypes

People tend to use various privacy management strategies to greater or lesser extents



de-identification of server data is still a good security practice, as it would take considerable effort to re-identify all users if the server is compromised.

COLLECTING LEARNER DATA

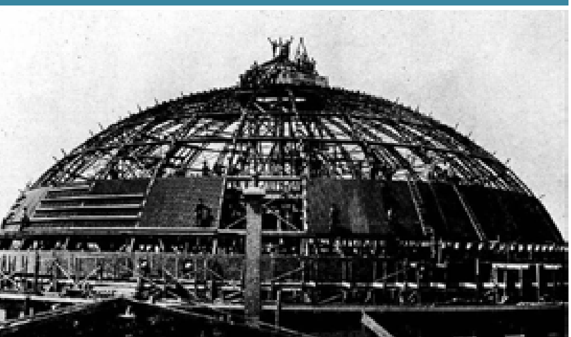
Digital learning systems have an opportunity to collect a wide array of data about their users. Long-term persistent data tracking allows learning systems to personalize learning and uncover useful insights about the learner base. However, each type of data also has unique privacy implications that must be considered. At the most granular level, digital learning systems can collect "learner runtime activity"—users' step-by-step actions that can be used to track users' progress and to adapt the learning experience to their specific abilities, knowledge, and pace.

Continuous tracking may create a digital *panopticon* that restricts user freedom. Therefore, users should be given easy-to-use notice and control mechanisms to manage the boundary between leisure and learning. Additionally, users' runtime activity should be carefully protected through a combination of strict access control, de-identification, obfuscation, encryption, and/or client-side personalization (see later sections).

INFERENCES

Learners' privacy concerns can also be impacted by the inferences made about them by the digital learning system. Users of personalized systems are negatively impacted when these systems make incorrect inferences about them. Even when inferences are correct, they may not always be wanted by the learner or be in their best interest. For example, research has shown that people are intuitively uncomfortable with the idea that sites track their data,[11] which may reduce their trust and negatively affect their disclosure behavior. Theories and recommendations for self-regulated learning practices should be incorporated into the trust-building requirements during the development phase.

panopticon / pan·op·ti·con / *noun* – a circular prison design, built for surveillance; so that all (*pan-*) inmates could be observed (*-opticon*) by a single watchman at all times—and so inmates knew they were always being watched.



OUTPUT MODALITIES AND DEVICES

Future digital learning systems are envisioned to be pervasive, multi-device experiences that might include smartphones, smart TVs, e-books, smart watches, and a multitude of other devices. These devices each present unique privacy considerations. Personal devices, such as smartphones and wearables, are ideal for real-time learning but can also create distractions. Therefore, learning experiences on such devices should be structured such that they don't disturb learners or reveal information about them in uncontrolled ways (such as a push reminder displayed as a popup—while projecting to a group from a smartphone). Strategies for achieving this include planning notifications carefully, avoiding interruption of a learner's current task, and adapting notification timing to the learner's context. Devices that are shared by multiple people (e.g., smart TVs) should also avoid leaking personal information in social settings. To do so, notifications on such devices should provide generic recommendations that mask details unless they are requested by the learner.

DATA LOCATION AND OWNERSHIP

A typical reason for integrating learning experiences in a distributed platform is to provide recommendation and adaptation capabilities across these learning experiences. This requires the implementation of data collection and storage facilities, communication channels, and adaptation capabilities. In most systems, these components will be centralized, so building trust between the learner and these components is extremely important. This can be done by

putting these components under control of a trusted, local entity, such as a single department or organization. However, this may also shield the components from important insights that can be gained from data collected across instances, and it may make the mobility of learner data more cumbersome.

Instead, one could build a learning platform where all users, departments, and organizations share the same centralized components. However, a single entity that collects the data of all users creates an attractive target for hackers.[12] A good trade-off is therefore to put these components at a level that is "low" enough for learners to trust but high enough to allow efficient mobility and user-modeling synergies. In other words, data/insight mobility problems can be reduced through portability requirements and standardized APIs.

Another question is how each learning application on the platform can access learners' data. Since users are likely to trust different applications to different extents, an access control mechanism is needed to allow applications to optimally utilize the learners' data while at the same time respecting each learner's privacy preferences. A recent development in adaptive systems is to perform the calculations required to compute adaptations "client-side" rather than on a centralized server. Research shows that such client-side methods al-

> We think there's a big opportunity to open that data up to an ecosystem concept. For example, predictive analytics can help identify who will do poorly or who will do well in courses…but should we show that to students? Will we create a self-fulfilling prophecy? It's important to consider the possible unethical deployment of this. The way to avoid it is to use a governance system to manage the data systems and be thoughtful about this.
>
> **Phill Miller**, Chief Learning and Innovation Officer, Blackboard

leviate privacy concerns.[13] However, client-side adaptation methods can only use limited inference methods (e.g., if-then rules, simple classification), and research has shown that users are concerned that their data can be hacked if their device is stolen, and that their user model is lost forever in case they lose or break their device.

Given these considerations and limitations, we suggest a three-tier data management and personalization approach: On the first tier, learner competency data is used by the platform to decide what learning applications to recommend to the user (meta-adaptation). On the second tier, individual applications can use similar data—albeit with regulated access control—to make app-level adaptations (macro-adaptation). Finally, on the third tier, client-side mechanisms can use fine-grained learner runtime data and behavioral tracking to make subtle adjustments to the learning experience (micro-adaptation).

DATA OWNERSHIP AND STEWARDSHIP

The end-user license agreement of most modern online services claims full ownership over the personal information they collect about their users. The legality of this claim is questionable though: The legal concept of "owning information" is still new, and laws are still being written about this topic. Moreover, preliminary investigations among users show that there are merits in granting end-users ownership of their personal information, and it may expedite the movement of data among different digital learning systems. However, data ownership is not exclusive, and it may be desirable to give other entities (e.g., applications, employers, researchers) partial co-ownership over an individual's data. These co-owners should request minimal amounts of data, avoid duplicate storage, and de-identify data where feasible.

Data ownership puts an important responsibility on the shoulders of the learners. It allows them to play an active role in making sharing decisions about their data, but not all users may be motivated and capable of taking on this responsibility.

In the 401(k) model, learners formally own the data, but they can partially delegate the responsibility of making decisions regarding their data to a fiduciary, such as a teacher or administrator. As a "data steward," this fiduciary would then be allowed to make decisions on the learner's behalf; although, there should be a strict policy that outlines the limits of these powers. This policy can outline several practices that are always allowed, never allowed, or require the explicit consent of the user. In the latter case, such consent should not just be a notice with an option to "opt out." Rather, it should ask the user to formally opt-in to the proposed practice—this practice makes it more likely that learners will make an informed consent decision.

Structure data ownership like a 401(K)

Finally, when more than one party has a say over the disclosure and use of certain data, Private Equality Testing can be used to create a Two-Person Concept solution (a concept proposed by U.S. Air Force Instruction 91-104 [16]) that prevents any single person from intentionally or unintentionally leaking data or becoming victimized by extortion or social engineering attacks.

Data Sharing

Data collected in digital learning systems can be used for purposes outside the system. One such purpose is to make the data available to the learner themselves, which allows *quantified self*–like innovations. Beyond this, learning systems can allow learning materials, activities, and outcomes to be shared with fellow learners (enabling social learning experiences), researchers (catalyzing learning innovation), and employers (informing organizational decision-making). This section covers the privacy-related consequences of the social, academic, and organizational use of data collected and generated by digital learning systems.

QUANTIFIED SELF

By sharing learner data with the learners, themselves, digital learning systems can create a "quantified self" experience that allows them to gain insights into their own data. For example, carefully constructed personalized infographics can allow individuals to explore the common and unique sides of their identities.[14] Such insights are an important reason for many people to accept the potential privacy intrusions that come with wearable technologies and constant tracking. As such, the quantified self can be a motivating factor behind the data collection efforts of a digital learning system. Also, the quantified self can be a catalyst for learning. Translating self-tracked parameters into a game-like structure can create new motivational and heutagogical support structures that encourage and enable users to push themselves further.

SOCIAL LEARNING EXPERIENCES

Sharing learner data across learning environments can, in some cases, be considered a violation of regulations, such as the *Family Educational Rights and Privacy Act* or *General Data Protection Regulation*. Hence, care should be taken that the learner (not the system) makes the decision to disclose such information. Even learners willing to share might not want to share with all of their contacts because they could be bothered by an overload of social activity.[15] As such, users should be allowed to select a subset of their contacts for sharing purposes, and the learning system can actively help them in this process.

RESEARCH AND ORGANIZATIONAL DECISION-MAKING

Learning data can also be used for research and organizational decision-making. Privacy experts argue that secondary use of information should be explicitly communicated to users, otherwise they may be surprised to find out about it and feel that their privacy is violated.[16] Moreover, there are laws and regulations surrounding research and employment-related practices that need to be adhered to. For example, whereas employment discrimination is ille-

* Heutagogy = study of self-directed learning

gal, algorithmic decisions have been shown to incorporate unwanted biases. Therefore, ethical considerations need to be made before using machine judgment for, e.g., promotion decisions.

Privacy Support Mechanisms

Several techniques for privacy support can be implemented in digital learning systems. This final section discusses their benefits and shortcomings.

PRIVACY NOTICES

Online privacy policies are often written in a legalistic, confusing manner and require a collegiate reading level to understand them. Indeed, while many people claim to read online privacy policies, many don't actually review them or don't read closely enough to understand them.[17] A lot of work has therefore gone into summarizing privacy statements, but summarized privacy notices are often too simplistic to accurately represent the policies they reflect.[18] One way is to add textured agreements, which add layers of emphasis to make the text more readable,[19] but these have been shown to increase (rather than decrease) the amount of time people spend reading the agreements. Although the consensus is that people should be informed about the privacy decisions they are asked to make, the reality is that doing so often makes them more fearful or unwilling to come to a decision. The conclusion, then: It's better *not* to rely on *any* privacy notices, but to instead make the privacy decisions themselves simpler.

CONTROL MECHANISMS

Simple privacy controls can help users take control over their privacy settings. For example, in social sharing settings, recipients can be grouped to simplify the decision landscape and graphical representations of the control matrix can help users understand and manage their sharing patterns. Selective infor-

mation sharing is just one of many strategies users may employ to alleviate privacy tensions. Likewise, privacy control can be provided in more diverse and intuitive ways than a traditional "sharing matrix" in which users specify who gets to see what. Research has found that it's important to give users the privacy features they want, lest they experience reduced connectedness and miss out on social capital.[20]

Unfortunately, while users claim to want full control over their data, they often avoid the hassle of actually exploiting this control[21]

In combination with overly permissive defaults, users' avoidance of control mechanisms leads to a predominance of over-sharing. In order to facilitate control, digital learning systems should use smart default settings and make the available controls as simple as possible.

PRIVACY NUDGING

Nudges are subtle yet persuasive cues that make people more likely to decide in one direction or the other. An example of a privacy nudge is a justification that makes it easier to rationalize a privacy decision. Justifications include providing reason for requesting the information, highlighting the benefits of disclosure, appealing to the social norm, or providing a symbolic character to represent the trustworthiness of a recipient (e.g. a "privacy seal"). Another approach to nudging users' privacy decisions is to provide sensible default settings, which tend to nudge users in the direction of that default.

The privacy nudges evaluated to date usually only work for some users, however, and they leave others unaffected or even dissatisfied. Some researchers argue that this is because nudges take a "one-size-fits-all" approach to privacy.[22] Since such nudges are rarely good for everyone, they may actually threaten consumer autonomy. It's therefore best to only use nudges if there's

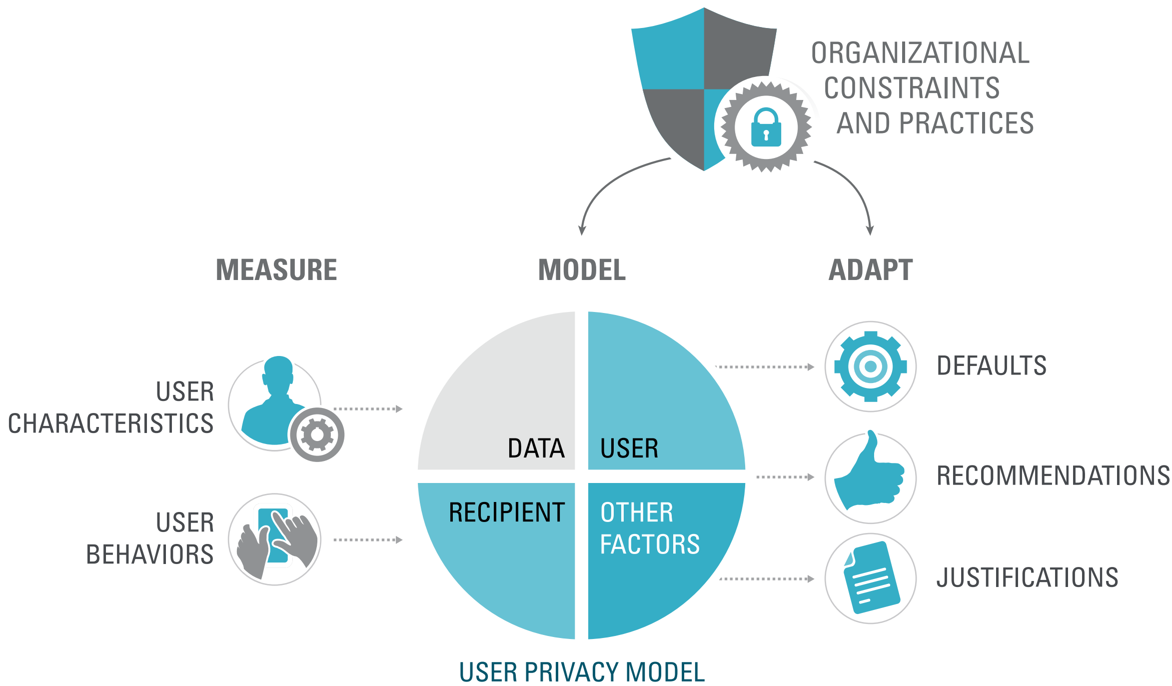


Figure 8-2: A schematic overview of user-tailored privacy

User-tailored privacy aims to strike the balance between giving learners no control over or information about their privacy at all versus giving them full control and an overload of information about it.

TWO EXAMPLES TO HELP ILLUSTRATE THE USER-TAILORED PRIVACY CONCEPT

1. A digital learning system normally tracks users' location (Data) in order to give context-relevant training exercises (Organizational practice). However, user-tailored privacy knows that like many young mothers (User characteristic), Mary (User) does not want her location (Data) tracked outside work hours (Other factor). It therefore turns the location tracker off by default when Mary is not on the clock (Default).

2. David needs to decide how to share his recent milestones—two certificates he's just earned (Data)—within his organization (Recipient). Due to the rules of his employer (Organizational constraint), user-tailored privacy requires him to share these milestones with his direct supervisor (Recipient). Moreover, from his previous interactions (User behaviors), the user-tailored privacy knows that David keeps close ties to several other divisions. User-tailored privacy therefore suggests (Recommendation) that he should share his new certifications with the heads of these divisions (Recipient) as well, explaining that they're likely to be interested in exploiting his newly gained skills (Justification).

consensus among learners about privacy. In these situations, nudges apply privacy by default but give learners a choice in the event that they want a different setting after all.

USER-TAILORED PRIVACY

User-tailored privacy is a novel means to support users' privacy decision-making practices.[23] A user-tailored privacy–based system first measures users' privacy-related characteristics and behaviors, then uses this as input to model their privacy preferences, and finally adapts the system's privacy settings to these preferences (see Figure 8-2).

The first step to user-tailored privacy is to measure learners' privacy-related characteristics and behaviors. To accomplish this step, learning system developers should acknowledge the plurality and multi-dimensionality of users' decision-making practices. They should also note the variability of learners' privacy practices; although, these can often be captured by a concise set of "privacy profiles," and, similarly, the potential data recipients can often be organized into a number of groups or "circles."

The next step is to model privacy. This can be done in a way that matches the learners' current privacy practices; however, in some cases, it may be better to suggest privacy practices that are complementary to their current practices, and in still other cases, it may be best to completely move beyond learners' current practices. The model can also take the practices and constraints of users' organizations into account. Finally, using this user model, user-tailored privacy can personalize the privacy settings of a digital learning application as well as the justifications it gives for requesting certain information, its privacy-setting interface, and its learning recommendation practices.

Arguably, user-tailored privacy relieves some of the burden of the privacy decision from a learner by providing the right privacy-related information and right amount of privacy control, without being overwhelming or misleading.[24]

Implementation Recommendations

We recommend several steps in the development process that will both build intuitive privacy controls into the design of the learning ecosystem as well as create privacy-sensitive recommender agents to guide learners.

1. DECISION-MAKING

Build trust: Ensure that the learning applications originate from trustworthy sources. Employ sensible data collection practices and a privacy-by-design philosophy from the outset. Finally, provide contextualized privacy control mechanisms and easy-to-understand privacy information

2. COMMUNICATION STYLE

Tailor to different privacy management strategies: Give *Selective Sharers* the ability to selectively expose data to specific apps and groups of people. Allow *Self-Censors* to use non-personalized mechanisms for selecting learning material and to restrict their forms of sharing. Allow *Time Savers* to opt out of active notifications and social features. Give *Privacy Maximizers* all of the functionality; *Privacy Balancers* mechanisms for curation, blocking, and avoiding direct interaction; and *Privacy Minimalists* adaptive and social functionalities within the ecosystem.

U.S. FEDERAL AVIATION ADMINISTRATION

"What we found when we studied the FAA is that the lines between training and operations are blurring. ...Aircraft have sensors with analytics; so, they can make profiles and tell if pilots do something unsafe. It allows the FAA to look into a program to provide information back to pilots. But the pilots, being union-driven and structured, said "No, you can't watch us!" So, they made a union the go-between guardian for that data. This way, if there is an issue, there are a series of approvals and guardians of the data, so that the pilot can't be punitively damaged but can be informed." – Michael Smith, Senior Technical Specialist, ICF

Real-world Example

3. LEVELS OF IDENTIFIABILITY

Devise appropriate levels of identifiability: Use, but do not rely on, de-identification for privacy purposes while allowing creative and (self-)evaluative environments to use pseudonymity. Formal and diplomatic settings should enforce a real-name policy.

4. COLLECTION OF DATA TYPES

Protect learner runtime activity: Reduce unfettered context tracking to prevent the creation of a digital panopticon, and provide easy-to-use notice and control mechanisms to control the boundary between leisure and learning. Protect learner runtime activity using access control, encryption, de-identification, and obfuscation and, where possible, process and use learner runtime activity data locally.

5. OUTPUT MODALITIES AND DEVICES

Don't disturb the user: Plan notifications carefully and provide easy controls for notification urgency. Adapt notification timing to the learner's context.

Prevent leaking personal information in social settings: Provide generic notifications that do not reveal (potentially sensitive) details and change the amount of information provided in each notification depending on the number of people who are near the learner.

6. MANAGE ADAPTATIONS

Implement the centralized components of learning platforms at the appropriate level: Put centralized learning components under the auspices of a trusted entity and support the portability of learning models. Allow for interoperability of learning applications through standardized APIs.

Regulate access of individual learning applications to the centrally collected data: Allow learning applications to do their own adaptations and put access control mechanisms in place to regulate the use of centrally collected data.

Use client-side micro-adaptation: Collect and analyze learner runtime data in client-side applications. Prevent the unnecessary storage of this data, and handle it in an ephemeral manner to prevent data loss or theft.

7. DATA OWNERSHIP AND STEWARDSHIP

Give learners ownership over their data: Allow learners to peruse their raw data and user models, and enable them to take their data with them across different learning institutions or employment organizations.

Give employers and learning applications limited co-ownership: Allow employers and learning applications to co-own appropriate data while requesting minimal amounts of data. Avoid duplicate storage and de-identify data.

Allow learners to designate a "data steward": Allow learners to delegate responsibilities to a "data steward" to manage their data under a fiduciary policy, and implement the Two-Person Concept using Private Equality Testing.

8. SOCIAL LEARNING EXPERIENCES

Give users control over what to share: Refrain from sharing any learning outcomes with others by default. Instead, require an explicit decision from learners before sharing learning outcomes with others. Allow learners to limit their connections to those they deem relevant for each application and implement a "learning buddy" recommender.

9. RESEARCH AND ORGANIZATIONAL DECISION-MAKING

Let learners know about secondary data use: Communicate secondary data use practices to learners and indicate exactly the data used and its purpose.

Act responsibly regarding research and organizational decisions: Anonymize research data, and make sure that promotion decisions are made in a non-discriminatory manner.

10. PRIVACY NOTICES

Increase the chance that learners read privacy notices: Use privacy nutrition labels to give learners a quick overview, and make notices textured to emphasize the details. Make the privacy notices attractive and approachable, such as by using use comics, and similarly, make the decisions simpler—ideally, to the point that notices are no longer required.

11. CONTROL MECHANISMS

Use accessible, graphical privacy controls: Make controls obvious and easily accessible. Use graphical methods to give users easy-to-understand controls, beyond just information access. Use a privacy setting interface that works for everyone (where possible) and keep it simple.

12. PRIVACY NUDGING

Use nudges if there is a consensus: Use justifications and defaults when virtually all learners agree on the optimal privacy setting, and incorporate nudges to provide learners choice in case they want different settings.

13. USER-TAILORED PRIVACY

Employ user-tailored privacy to support learners' privacy decision-making practices: Measure learners' privacy preferences in context, exploiting their multi-dimensional nature. Carefully balance recommending current, complementary, or novel privacy practices as well as proactive and conservative adaptation strategies.

CHAPTER 9

ANALYTICS AND VISUALIZATION

Shelly Blake-Plock

Analytics and data visualization are now mainstream. The maturation of cloud services and the adoption of new web technologies have accelerated both fields. Among the most important innovations has been the development of new streaming data systems. These technologies can handle the exponentially increasing scales of data produced—not only by traditional web and social media technologies but also by machines and sensors deployed in cyber-physical systems such as consumer wearables, smart city implementations, and connected industrial devices.

This chapter summarizes the state-of-the-art in streaming data, learning analytics, and data visualization for non-technical readers. It provides context, lays out a vision, and provides high-level guidance on implementation approaches. The goal is to provide practical knowledge to teachers and trainers, business users, and programmatic decision-makers, helping them to envision how learning analytics and visualization can increase the capacity of learning organizations as well as the general approach to such implementing systems.

What are we talking about?

There's so much data in the world. Each of us produces a cloud of "data exhaust," with every mouse click or upvote. Learners, too, generate masses of data—information that could inform education and training if we could access, analyze, and meaningfully visualize it. Two closely related fields—educational

data mining and learning analytics—are providing tools to meet those goals.

Both fields differ slightly, for instance, based on their origins, primary application areas, and preferred AI algorithms.[1] Learning analytics grew out of efforts in the semantic web, and it's practitioners tend to emphasizes big-picture analyses and decision-support for teachers and learners. Educational data mining developed out of the adaptive instructional technologies tradition, and it tends to focus on automated adaption and reductionist modeling.[2] For our purposes, in this chapter, we're less concerned with the finer details distinguishing the two disciplines. Instead, we're focused on their shared purpose: Understanding and applying data-intensive approaches to education and training, particularly for large-scale learning data—so called *big learning data*.[3]

As the phrase "big data" implies, training and education analytics often (but not exclusively) employ machine learning techniques. Machine learning is a subset of AI that uses algorithms to automatically uncover patterns in data to, for instance, assign classifications, estimate the influence of different variables on downstream outcomes, or make predictions based upon historical data. In the training and education domain, these applications have notably matured over the last 20 years, coalescing into the two communities mentioned above.

But what can you *do* with these tools? People have applied analytics to a variety of learning systems. For instance, some applications use analytics to predict engagement and then recommend personalized resources to encourage students' participation.[4] Others can analyze students' interactions and proactively alert instructors as to which may need help.[5] One well-known example, Purdue University's *Course Signals*, used current data from an LMS combined with historical data (such as course attendance and prior grades) to forecast which students would fall behind in a course and then alert both learners and their teachers about their risk levels.[6] Other tools apply similar retention management approaches across an entire student body, identifying those at highest risk of dropping out—in time for the administration to intervene.[7] Basically, any of the analytics applications we've come to expect of

e-commerce systems, from time-sensitive personalized recommendations to system-wide trend analyses, can translate into analytics for learning.[8]

DIP YOUR TOE INTO THE STREAM

Streaming-data analytics is a uniquely exciting and freshly emerging subfield within analytics. When we say streaming data, we're generally talking about a range of data types that are event-based and track some variety of activities, whether human or machine in origin. The invention of streaming data has impacted the way we think about what data, itself, represents as well as how it's leveraged to guide human insights or automated machine processes.

For instance, in the domain of sales and marketing, event-based data has increased our capacity to understand the market and prospective customers. It provides a window (for example, via analysis of social media streams) into the story of the prospect's journey, both as it relates directly and indirectly to a product or service offering. In the entertainment industry, streaming data informs recommendations of content, such as movies and television shows on Netflix. In politics, streaming data helps analysts identify and capitalize on public sentiment and social trends.

Data-stream architectures are contrasted against traditional batch-processing systems. Data streams are characterized by data moving at a high velocity. They also have strict constraints for processing the incoming data online, within limited amounts of memory and time, and they must always be ready to provide analytical predictions when queried.

Just as these technologies and data architectures have transformed business, entertainment, and politics, so too are they able to transform learning. In the learning space, the availability of activity-based data streams offers an opportunity to trace and understand learners' journeys. Analytics in the service of these streams of data can provide accessible, automated, and near real-time data visualizations, as well as trigger alerts and interventions based on key performance indicators. These journeys—which comprise learners' activity and behavior profiles—can be considered *highly formative*, quantifiable micro-assessments.

Digitizing the Analog World

We often see a desire to digitize the analog world. We wear digital watches that resemble their windable cousins. We create "offices" in our computers, mirroring the components of the physical workplace. In education, we digitize chalkboards, loose leaf, and books. But the inclination to recreate the analog world within the digital domain eventually confronts both the limits of analog practice as well as the more esoteric surprises of what, when it works in our favor, we call innovation. When we move from tangible "things," such as chalkboards and books, to conceptual practices and processes, such as assessment, the situation gets particularly dicey. Esoteric and nuanced concepts become oversimplified to the point of caricature. This leads to notions being thrown around such as, *AI will replace educators!* or *Automation could never substitute for teachers!*—arguments that tend to betray a misunderstanding of both AI and teachers. However, in the world where access to learning is distributed across the internet, expansive in breadth and always available, there are practical limits to the analog approach of teaching. While there's little danger that AI will "replace" human teachers, their role—and the way we implement training and education, writ large—needs to evolve in collaboration with evolving technologies.

* See SAMR model in Chapter 3

In a world that needs learning at scale, the real conversation should be, how can AI serve the needs of teachers—and vice-versa?

Data at Scale

Contrast the analog "data set" with the contemporary "data assets" created by social media newsfeeds. These data assets support the creation of time series–based behavioral profiles that hold the activity records, built up over time, from users' behaviors on social media platforms, including likes, comments, shares, photo posts, video watches—all user actions. These become part of the user's behavioral profile, and, in turn, become nodes on a vast social graph. Each node owns a narrative. That data asset is key to the social media industry's business model. It's the aggregate of these profiles that creates the opportunity for more targeted advertising, and, at scale, it's a most impressive record of formative experiences—of individuals, yes, but more so of vast aggregate populations.

For social medial data assets, value isn't encapsulated in a single pinpoint score. It's not even found in the ability to estimate a single user's likelihood of accepting a given advertisement (although this certainly brings some benefit). Rather, or (at least) more importantly, value derives from the cumulative amalgamation of all these behavioral profiles. The power is in the aggregate. Only the scale of the aggregate provides the rich raw data necessary to uncover the array of patterns, categories of human interest, and shared narratives of human experience. It's a matter of scale. Similarly, the challenge streaming data poses to the traditional view of assessment comes down to a matter of scale. A gradebook at scale will never offer the insights into learning experiences that an activity feed at scale can provide. This isn't to denigrate gradebooks; rather it's a reminder to recognize their functions and where their value lies.

Consider a typical gradebook full of letter grades and percentages. In one sense, this table of letters and numbers offers a substantial bit of information about how one student may have progressed over time or how she compares to her peer group's scores. But in another sense—in the sense informed by a world of streaming data, where data convey a narrative about students' digital experiences—the gradebook tells us little about what actually happened, how it was done, and what it suggests about the learner. The gradebook, and the modes of assessments that inform it, are analog technologies. They're no worse than digital technologies merely because they're not computerized, but they are technologies reflecting an earlier paradigm—a paradigm ill-equipped to support learning at scale in a digitized, interconnect world.

...people don't drive cars because they hate horses

Supporting Decision Making

Learning practitioners have long sought to increase their insights into formative development. For instance, teachers may subconsciously wonder, *How far along is each student in his or her learning journey?* Unfortunately, difficulty in gathering the data points needed to make confident and continuous formative appraisals makes the alternative—a big summative assessment—seem like the only option. This can be understood as a scale problem. Yet, by leveraging activity and event-based data in a manner similar to what social media employs, we can create formative profiles of learners. These, in turn, can empower (human) educators and trainers to make better decisions about instruction and help them tailor guidance in ways that would otherwise be impossible. We can similarly empower learners, administrators, systems teams, content and experience providers, and a whole host of constituents across the learning ecosystem with information relevant to improving, and making more meaningful, their own pieces of the puzzle.

The result of this merging of activity and event-based streaming data, along with the subsequent human applications of the knowledge derived from it, could offer a path towards something of a Golden Age for formative assessment—but this Golden Age doesn't stand a chance if either the technologies or instructional strategies employed fail to attend to the matter of scale.

A challenge, therefore, is to reconceptualize assessment from the point of view of learning at scale, as opposed to its traditional analogs found in "un-scaled" contexts. Computational learning analytics are core to this conversation. Any notion of assessment in the digital world must consider the impacts of scalable, continuous, multifactor data. The future of assessment is analytics.

The time is ripe to investigate new models of assessment that take advantage of advancements in cloud services, streaming data architectures, APIs, and a new generation of web-based applications. By applying these tools to

> One key topic of focus for future learning is data analytics. We currently use very fanaticized or ritualized measures, like time on task or changes in knowledge in a single area. How do we get that mind reset to the galactic view of learning?
>
> **Elliot Masie**
> Founder, The MASIE Center

learning, we can surface meaningful patterns previously too obscure, if not overly complex, to act upon.

This prompts us to consider a wholly new human-machine model of assessment for the digital age, not simply a digitized version of analog assessment at scale. For example, it's routinely noted that automation can maximize the efficiency and timeliness of tactical learning interventions (e.g., micro- and macro-adaptations). However, automation can also help identify those interventions best addressed by a human—who, in a web-scale context, needn't be a single preassigned instructor. Rather, learners could be served by a distributed network of potential teachers and mentors, and based upon various automated analyses, the system could recommend the optimum (human) learning facilitators for different situations (including, potentially, the individual learners, themselves). In this way, we enable widespread distribution, not just of individual instruction, but of the entire ecosystem—including its human capital.

This suggests a new paradigm for learning and assessment, one where machines and humans complement one another—a symbiotic system.

In addition to automating the collection and analysis of data, it's possible to automate its visualization via learning analytics dashboards.[9] The idea proposed here is to fully leverage activity and event-based data to provide 360° views of learners in real-time.

These dashboards could readily visualize concepts, such as:

- Frequency, time, and duration of individual, cohort, global activities
- Frequency, time, and duration of engagement with specific content
- Outliers among actors or content, in terms of level or type of activity
- Relations between actors, such as shown by a directed network graph
- Individual or cohort performance aligned to KPIs or business goals
- Recommended interventions to support learners' progress
- Trends among content engagement activities and learning pathways
- Outliers among actors, in terms of similarity or dissimilarity of content usage, types of engagement, or times and durations compared to a cohort or global group

Further, in future iterations—once enough relevant data points have accumulated—machine-learning algorithms could help uncover common learning trajectories or the factors that make different pathways more or less effective for different categories of learners. These sorts of activity patterns could be visualized, for example, by using heatmaps to depict which instructional content successful learners spend the most time with or by using polar graphs to indicate the behavioral trends exhibited by learners of different aptitudes as they interact with a given learning object (e.g., fast-forwarding through parts of a video or abandoning a simulation at certain times). For learners, dashboards can help individuals visualize their own gaps and proficiencies, and help them take steps towards managing their own learning.[10] For administrators, these algorithms could help forecast enterprise-level planning issues, inform education and workforce strategic-level decisions, or suggest incremental improvements for the system itself. Ultimately, a "mission control" dashboard comprised of modular data cards—each representing different insights and each providing ways to query the data—could be available to each "persona" with in the learning ecosystem, including for learners, instructors, content developers, administrators, and policymakers.

It's almost cliché to say, "learning is a journey." But when most people use this platitude, it's possible they really mean, "Sure, you're going to find out new things in the future, but *this* class ends in three weeks and you'd better finish *this* learning by that time." An assumption of the learning ecosystem concept, and the closely related philosophy of personalized lifelong learning, is a shift away from output-focused, time-based learning—characterized by high-stakes summative tests—and instead towards more a process-focused outlook on learning—supported by a steady stream of formative assessments. This represents a fundamental shift for learning and assessment—away from discrete mathematics and towards continuous equations.

IMPLEMENTATION RECOMMENDATIONS

Because the field of streaming data and the capabilities it supports are still emerging, we expect future innovations to eclipse the suggestions made in this chapter. But in terms of a starting point, the section below outlines practical implementation steps to consider when looking to bring this new wave of digital transformation to bear.

1. Needs Analysis and Data Assessment

As in most processes, the first step involves problem framing. Determine what outcome data are needed and what types, quality, and amounts of data are already available. Ask questions to identify factors, such as the state of current and historical data assets and data-producing sources, both within and external to the current system as well as the status of currently accessible

data, including the shape of the data model and where, when, and how it was delivered and stored. Also document the status of the current data architecture and system design, and information about its previous incarnations (if any), including its historical levels of use and expectations for the scale to be served by the new system. Finally, as appropriate for any project, catalog the known risks and protocols (such as privacy, data governance, and security); the objectives and goals of digital transformation, so as to provide guidance on what new data sources will need to be integrated into the system to provide desired metrics and insights; and the timeline, scope, and budget, in order to best enable (what will most often be) a phased approach to implementation of the complete system.

2. Data and Visualization Designs

Practitioners often make mistakes during the data design phase that only surface later in the process. To limit exposure to errors, poor design, and the accumulation of technical debt, it's useful to work backwards. Begin by laying out key questions; simultaneously, it's helpful to draw prospective visualizations for these questions, particularly in collaboration with their respective end-users. Next, identify performance indicators that provide insights to those questions, and determine what data sources may best inform these performance indicators (whether or not those data sources currently exist). Then design the "ideal" data model, incorporating the hypothetical data sources previously identified; take care to deliberately consider how different data sources may react to one another and how data from multiple sources may be needed to inform recommended actions—possibly including actions taken by other providers within the larger ecosystem. Once this optimum data model is developed, look for available data sources to fill, or at least partially address, its proposed components; also, consider potential limitations or access issues with these data. Finally, revisit and tailor the visualization mock-ups to the final data model.

There are a variety of ways to visualize data. Key factors to consider include the velocity of data streaming through the system, the shape of the data, semantic features including both human- and machine-readable attributes, potential correlations or potential false flags among the data, and the metrics necessary to demonstrate progress towards key performance indicators. Additionally, strive to design visualizations to be as transparent as possible, to help end-users build appropriate levels of trust in the algorithms and make informed decisions based upon the analyses they depict.

Related concerns, such as privacy or access to data streams, should also be considered during the design phase. Adhering to industry or organizational policies, such as learner privacy rules, may limit the ability to create a robust profiles. Sparse data may impede the ability to generate analytics using many established big-data methods. It's important to realistically scope the data model and visualizations to a realistic volume and robustness of data, and to determine the minimum amounts needed to produce useful insights around the identified key indicators.

3. Architecture Development

Once the conceptual data model is designed, the next step is to develop it.

To achieve the "future learning ecosystem" vision, learning applications need to capture and structure (or at least semi-structure) learner activity data, to support its aggregation and utility at scale. xAPI is among the most capable and flexible learning-data specifications for this purpose, and it can be leveraged alongside other data formats (either non-activity-based or from non-learning-domains) to provide a fuller view of learner experience.

When applying the xAPI specification to capture and store data, an xAPI Profile should be used, either an off-the-shelf Profile or, if none suffice, then a new one created for this system. xAPI Profiles define the accepted terms (or

variables) within a given implementation as well as their uses and semantic values. xAPI Profiles create clear, domain-based modeling structures that help define the scope of a project, making it easier to deliver human-readable data and provide navigable machine-readable data across the ecosystem. Profiles can also serve as a useful tool to ensure a clear alignment of business processes and learning objectives to the proposed data model before its implemented.

Next, choices will have to be made regarding the integration of other data sources. Some learning data sources already may be delivered natively in xAPI formats. These data will usually be validated and made available by a learning record store, a particular kind of datastore defined by the xAPI specification. Standardized data and APIs, such as those offered by xAPI, make data aggregation relatively easy. However, there may be other learning data or non-learning activity (such as on-the-job workflows across web services) that aren't natively structured as xAPI statements. One option is to instrument the external source to deliver xAPI data, but this can be difficult when working with proprietary third-party software. An alternative is to coerce the data into an xAPI format using API methods. However, it won't make sense to force all data into an xAPI-based data model. There's no reason to transform data into xAPI formats if it's not a good fit. Instead, this heterogeneous data either may be modeled to another specification or just passed directly through the Kafka Streams processor (described below), where it can be subscribed-to by different applications and joined with disparate data in downstream analyses.

Once the native data format and external data streams have been defined, they'll need to be implemented within a streaming data architecture. These can follow several models, but we would usually recommend the Kappa Architecture[11] as the software architecture pattern for a real-time learning ecosystem. This paradigm treats everything as though it were streaming data and processes these data into a stream that may be leveraged by various microservices. This approach generally makes it easier and more efficient to deal with various forms of data, as opposed to creating polyglot solutions and

maintaining a separate code base for batched and non-streaming data or—in the case of xAPI—each non-conformant data source or data type that may pass through the system (e.g., from student information systems, HR technologies, and legacy databases). In this architectural paradigm, regardless of the nature of the source, the data comes into the stream as logged events. This is a huge benefit to real-time analytics because from an operational perspective, the subscriber to the data stream never has to request that the data producer batch the data. Instead, the subscriber always has access to the log and can replay the events in the log as necessary to perform operations.

When considering the integration of data from different sources, it's important to carefully consider how users' identities will be handled. Identity management should be organized so that everything is kept orthogonal. When designing a streaming data architecture, it's also best to keep identity management and administrative provisioning matters close to the point of ingress; so that no data elements slip through unaccounted for.

As mentioned above, streaming architecture may be served by implementing an open-source stream processor, such as Apache Kafka.[12] Identity management and security applications will need to work in concert with the Kafka implementation. Once set up, data from all sources will flow into Kafka to be processed and sent down into a data stream. Data in that stream may be subscribed to by any application, such as business intelligence tools or a learning record store. The application listens to the stream and pulls out a copy of a piece of data when it recognizes it. Microservices provide these capabilities and help to automate data flow. Ideally, data will automatically go where they're supposed to; so that they can be analyzed, visualized, aggregated, verified, or so on, by various subscribed applications. Meanwhile, all of the original data passing through the stream eventually ends in a data lake, where it may be accessed and queried manually or via machine means later, as necessary. And, as mentioned above, all of the data is now available as logged events—which provides considerable operational efficiencies. This

> The system for military promotion is well known, albeit difficult to use. Whenever you get to a point of appraising someone's abilities, people become serious about what the metric is and how it is being collected. They want to know, "How do I achieve the metric?" They will focus their minds on the details of metric collection and if they don't get promoted, they will expect a debrief that provides clarity on why they missed the mark. They want to know with credibility; it can't just be a machine saying you just didn't get promoted/recommended. This is all part of treating them right. We will always need humans in the loop when dealing with human performance assessment.
>
> **James Robb**
> Rear Admiral, U.S. Navy (Ret.)
> President, the National Training and Simulation Association

stream processor model is in contrast to point-to-point architectures, where all applications within a learning ecosystem attempt to connect with one another, to exchange data bilaterally. Point-to-point architectures scale poorly.

Finally, a word of caution: Generally speaking, especially in enterprise scale implementations, we would refrain from using third-party SaaS integration solutions. They add cost and licensing complications, may affect throughput, and can be a burden in the event things break or the third-party ceases to provide the services. Third-party services can also create unanticipated security challenges. In our personal experience, it's almost always better to build natively or to provide data translation services of your own design.

4. Deployment

The fourth implementation step is to choose the deployment environment. There are a variety of commercial and specialized cloud architectures that can support streaming data. Depending on your needs, you'll likely be choosing between enterprise SaaS and Virtual Private Cloud instances and creating the templates to size them appropriately. On-premise deployment is an option, though it may greatly increase complexity and cost both during deployment and in ongoing maintenance.

Most implementations will follow a general pattern of alpha to beta to production deployment. As part of your alpha deployment, you should identify and address issues around privacy and security protocols, identity management and administrative provisioning, quality assurance, and continuous integration regimes. You'll also need to conduct systems testing. During the beta implementation and testing period, you'll stress test the system with real users; take this opportunity to identify bugs as well as ways to improve the user experience both for end-users and for those maintaining the system.

5. Production Implementation

Production implementation marks the beginning of a new phase. Depending on the volume and consistency of data, machine learning techniques (to potentially include deep learning approaches) can be applied to these real-world data flowing through the system. Deep learning processes could unlock a host of innovations in this space, including ways to link cognitive machine processes with biometric, decision-making, and event-based human learning activities.

Be warned, however, by their very nature, streaming architectures can be fragile. New product development by a vendor may break an endpoint. This will have to be fixed in order for the data from that vendor to be able to flow as

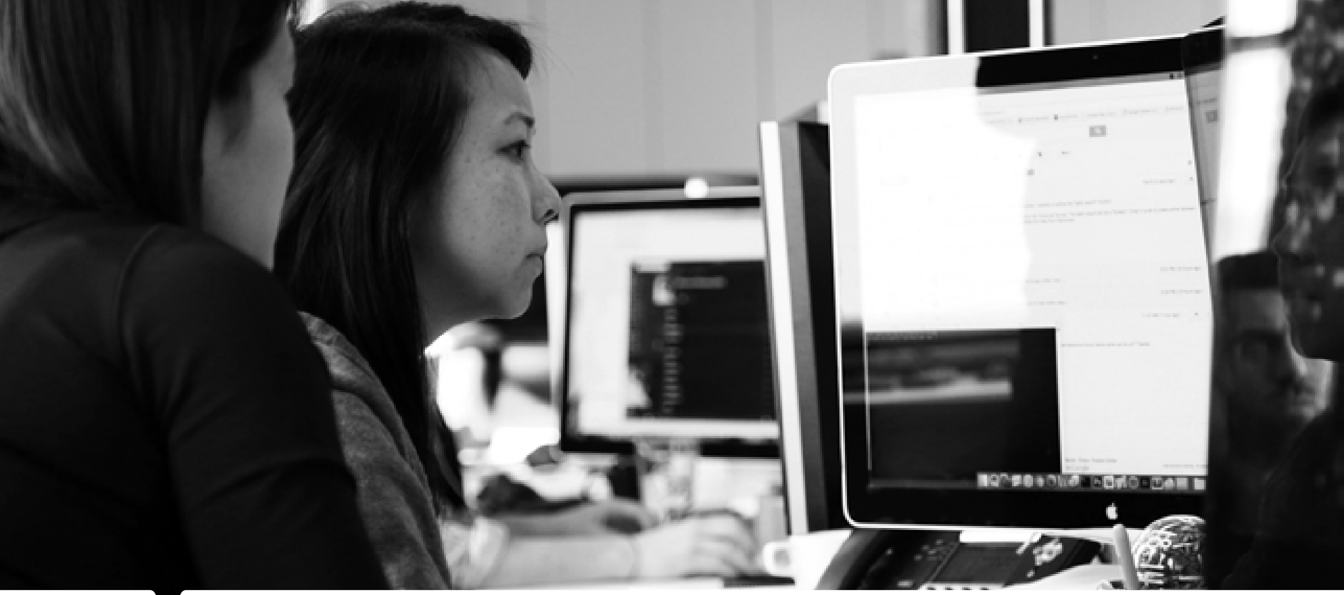
it is supposed to. Because other services may be depending on data from that vendor in order to process jobs, breaks such as this can cause bottlenecks that affect the larger system. For that reason, it's crucial that stream-processing systems be attended to by services teams, either locally or via managed services. Luckily, making fixes is usually a relatively painless process so long as you've done your due diligence into the quality of the data sources feeding into your system. Further, because most breaks will be caused by things like changes to endpoints or reconfigurations of APIs, they're usually well-documented and part of the product plan shared with the team—meaning most breaking changes will be telegraphed well in advance and can be planned for.

> Some practitioners use the acronym **FATE** when discussing Fairness, Accountability, Transparency, and Ethics in AI

Just as important to the success of the analytics and data visualizations services within the future learning ecosystem will be scalability and extensibility. Advances in learning tools, web technologies, and AI are likely to alter future learning analytics and data visualizations. Likewise social changes in behavior, expectations, methods of instruction, access to learning, and preferences among both formal and informal learners will influence the nature of the events captured in activity data streams. The technologies deployed to serve learning analytics and data visualization objectives, therefore, should be as flexible, extensible, and open, as possible. The systems must be built to withstand whatever is thrown at them. Dedication to open source standards and specifications will aid in meeting this need.

Conclusion

In the end, the quality of insights gleaned from analytics and visualizations will be tied to the quality of their data models, the velocity and variety of the



In a learning management system, you can get a gradebook, much like analog systems today but available online. But with the advances in assessment analytics, you can delve much deeper to gain insight into how reliably your questions and tests are measuring what they're supposed to measure. You can determine if your question bank is fair, valid, and reliable. You can see in multiple views in a dashboard, and you can even see it within, and eventually across, education, defense, commercial, and healthcare.

Stacy Poll

U.S. Public Sector Business Development Manager
Senior Account Manager, Questionmark

data they employ, and the accuracy of the data's representations. As the truism goes, there are *lies, damned lies, and statistics*.[13] Statistics, and even more so infographics and visualizations, when misapplied can obfuscate the "truth" of data. It's far too easy to make bogus claims, given any data set—particularly one as complex, personal, and socially and culturally situated as learning. Consequently, the design of the data, application of algorithms, and layout of visualizations are of great consequence. Small decisions during these design and development phases can lead to significant downstream effects—hopefully positive ones—for learners and other learning stakeholders.

CHAPTER 10

PERSONALIZATION

Jeremiah Folsom-Kovarik, Ph.D., Dar-Wei Chen, Ph.D.,
Behrooz Mostafavi, Ph.D., and Michael Freed, Ph.D.

Scientific studies show that personalized learning produces better outcomes than static, one-size-fits-all instructional experiences.[1] When instruction is personalized, learners show improved recall and better near- and far-transfer. Personalized learning can engender deeper understanding as well as hone higher-order cognitive skills, such as leadership and adaptive thinking.[2]

Customized experiences, like those a skillful tutor might craft, are the gold standard for learning, but these don't scale well, given the costs and limited availability of expert teachers and trainers. Computer-assisted instruction can mitigate scalability issues, and personalized learning technologies can (at least partially) unlock the benefits of one-on-one learning, similar to working with a personal mentor.[3]

Generally speaking, personalized learning technologies attempt to create different experiences for different learners (or for the same learner at different points in time). At the simplest level, this might involve customized settings based on individuals' preferences or differentiated instruction, where predetermined categories of learners receive different instructional packages (e.g., a system that offers unique pathways for novice and intermediate students). More notably, personalized learning can incorporate adaptive mechanisms—adjusting the learning experience based upon a stream of incoming data. This sort of adaptive learning is usually what's meant when people tout the benefits of personalization. (And, on the whole, this chapter focuses on adaptive learning, as well.)

> There are numerous ways that consumers are already experiencing personalization: Coupons printed at grocery store cash registers, dynamic home pages of e-commerce sites based on previous purchases and store browsing, personal-assistant capabilities, recommend restaurants, and driving directions to get there. Consumers now expect the benefits of those experiences in other online experiences—*like learning*.
>
> The personalization capabilities become a virtual concierge for learning experiences, making recommendations based on a combination of needs and interests of the learner.
>
> **John Landwehr**
> Vice President and Public Sector Chief Technical Officer, Adobe

Modern technologies increasingly employ a spectrum of personalized learning methods to tailor instructional elements, such as task selection and tutorial examples,[4] to better suit individuals' goals and characteristics, prior experiences, demonstrated knowledge and performance, environmental conditions, and/or social contexts. For example, as someone gains proficiency, a system may alter the order and frequency of problems, progression through the curriculum, and types of feedback given. Adaptive learning systems can help ensure learners have truly mastered each required objective, guiding them through activities that exercise and verify each of the enabling objectives and progressively scaffolding learners to reach mastery. Additionally, as evidence accumulates from multiple learners, some systems can use data-driven methods to identify trends, such as portions of the instructional sequence that are problematic or unintuitive. Other systems can use learners' behaviors to recommend peer-to-peer and team matchmaking, or to identify when a student needs human (versus automated) feedback.

Adaptive learning technologies, on average, produce substantially better outcomes than conventional, group-based or

non-adaptive learning.[5] Adaptive technologies can also make learning more efficient, delivering training and education in less time or at lower run-time costs. For instance, learners can spend less time reviewing material already familiar to them, and they can receive remediation as soon as it's needed. Adaptive systems can also use fewer, or at least shorter, assessments because questions can be carefully chosen to maximize their utility in estimating each learner's capabilities.

LIMITS OF CURRENT PRACTICE

While personalized learning has already been used in various settings, its full potential hasn't been achieved. Part of the problem is that these systems are typically designed to meet specific, narrowly focused instructional needs, and as such, their benefits tend to be localized. Widespread implementation of idiosyncratic solutions also means that methods of development, evaluation, and reporting are nonstandard. This makes the transfer of data between insular systems difficult, which limits the available adaptations and means that instructional episodes are likely to appear disconnected and inconsistent to learners.

Another challenge is their development costs, which, historically, have averaged around 100–300 hours of time—from highly skilled researchers, software engineers, and subject-matter experts—for each hour of learner interaction.[6] A significant portion of this time is spent building the learning and behavioral models that make automated adaptation possible. Considering the hundreds of hours of instruction needed for a single domain, along with the personnel and time required for its development and testing, the cost of personalization can be high.

When considering its many benefits as compared to current one-size-fits-all practices, however, even expensive adaptive learning offers an overall ad-

vantage. More than that, with the advancement of model-building techniques using machine-learning methods and the increasing availability of authoring tools,[7] development is becoming more efficient. Today, a modern system could be built with as few as 20–30 expert hours for one hour of instruction.

Overall, this field is fast growing, and new technologies are improving the sensitivity, impact, efficiency, and cost-effectiveness of personalized systems every day. The following sections outline a general approach to designing and deploying personalized learning, with a particular focus on how new adaptive learning capabilities will inform the future learning ecosystem.

DESIGNING PERSONALIZED LEARNING

When preparing to implement a personalized learning approach, it's useful to consider which aspects of a learning experience are most impacted by personal differences as well as how instructional elements might be varied in response to those differences. The availability of historical, real-time, and external data sources will also influence the adaptive system. The next three subsections step through high-level considerations for data collection, data analysis, and what and how to personalize learning.

Data Sources

Adaptation requires something to adapt to; this could include demographic and background information as well as real-time performance, sensor, and behavioral (event-based) data from learners. There may also be important contributions from information sources outside of the learner directly, such as contextual information and instructor inputs.

Relatively static data, such as learner traits and prior experiences, can inform simpler forms of customization, such as role-based differentiation, or help seed a new learner profile within a system. Some personal traits shown to meaningfully inform personalization include goal orientation, general self-efficacy, computer attitudes, and metacognitive abilities. Constitutional attributes, such as job title or military rank, can also be useful, in particular, because they're often easy to obtain and can somewhat substitute for past-performance information (if those data aren't available). Prior knowledge and skills, unsurprisingly, are among the most useful historical data for informing personalization.[8]

Learner performance data can include both static data, such as from historical test results and portfolio scores, as well as more timely data from quizzes, exercises, simulations, and other activities within the given instructional experience. Learner performance can be used to inform complex inferences, through methods such as item-response theory or Bayesian knowledge-tracing; simpler approaches, such as comparisons to threshold metrics and population norms, also provide some utility. However, even basic learner-performance data isn't always easy to collect; sometimes, for instance, individuals or organizations may feel threatened by the measurement and recording of their scores. Despite this, learner performance data makes a big difference to personalization; it's worth the effort to devise quality measures, collect the data, and analyze them carefully.

A new source of data available in some settings comes from sensors, i.e., devices that can measure physical or physiological information about learners objectively, removing some ambiguity surrounding the mediators and moderators of their performance. Some specialized sensors, such as galvanic skin response and heart-rate variability monitors, can detect learners' mental and emotional states (to an extent). What's more, specialty hardware isn't always required; low-cost sensors are already built into many devices, such as laptops and cell phones, and these can track location, context, gaze direction, pupil

> Different people have different strengths so how can we structure the training based on those differences? How do we deliver the required training in less time and have our military personnel better prepared when they come out the back end?
>
> Thomas Baptiste
> Lieutenant General, U.S. Air Force (Ret.)
> President and CEO, the National Center for Simulation

dilation, and various other inputs from voice, gesture, and posture cues. Data from these low-cost sensors has already been used to infer states such as stress, boredom, and confusion. Instrumentation within software can even use keyboard and mouse inputs, such as slower typing or repetitive mouse movements, to infer learners' attentiveness, engagement, or irritation, as well as help confirm a learner's identity or uncover signs of cheating.[9]

Related to both learner performance and sensor data, learner experience data refers to event-based data that describe what learners see and do. Compared to learner performance data, learner experience captures not just the outcomes but all the steps that explain each outcome—the fine-grained, step-by-step activities a learner (or other relevant human or machine agents in the setting) perform. These could include pausing a video, selecting (and then changing) a quiz answer before submitting, or requesting help from an automated tutor.

Important insights may also come from external sources, outside of the immediate delivery technology or instructional activities. For example, other social interactions, such as casual discussion boards in online courses, can be mined via natural language processing to learn more about learners' interests and attitudes or to inform social network analyses. Contextual information about the learning environment can also be used. For example, time and location data can be collected by learners' sensors and then integrated with external weather and map databases to inform real-time context-relevant learning examples. Similarly, logistical considerations may affect learning delivery con-

siderations; these could include the digital devices available to that learner (e.g., smartphone versus laptop), the number of seats available in a particular course, or cost and time constraints. Organizational factors may also inform personalization in various ways. As one example, consider how the design and delivery of learning might change depending on whether someone is completing a training course for workforce compliance reasons, because of professional development goals, or out of personal curiosity.

Another form of external data comes from human observations and inputs, including from learners themselves, their peers, instructors, and supervisors. For instance, an instructor might input a critique about a student's persuasive writing, or an observer/trainer might score exercise trainees against a performance rubric. A student may even self-report data, or it might come from peer evaluations or 360° surveys. (The point is, it's not necessary for all aspects of the future learning ecosystem to be digitized and automated! In fact, this is an important area for ongoing research, i.e., how to best integrate technology with learning facilitators in a symbiotic—rather than substitutional—way.)

Finally, it's important to note that learner data is often more useful when it's more robust, more personal, and more contextualized—but these same characteristics also increase privacy concerns. A balance must be carefully struck. (Refer to Chapter 8 for a more detailed discussion.)

Data Analyses

Collected data need to be analyzed in some meaningful way, and then the system should use those analyses to make diagnoses, predictions, and adaptation decisions. What kinds of decisions can personalized-learning technologies make? The most obvious answer is they can estimate learners' content mastery and then take actions to fill capability gaps and remedy misconceptions. People learn at different rates, and some of the most impactful interventions a system can make are simply to ensure each learner progresses at his or her

optimal pace so that all learners reach mastery, without skipping over important subcomponents or suffering through already-known materials.

Definitionally, mastery describes an estimate of a learner's competence, the true value of which is hidden from observation. Mastery results in observable performance, such as correctness and speed of responses.[10] Mastery estimates can be informed by static data from a learner's profile or demographic inputs, particularly initially. During a learning episode, mastery estimates are best informed by newly generated, contextually relevant data. Take care, however, to acknowledge the limitations of mastery estimations. Lucky guesses, accidental inputs, trial-and-error, and any number of accidental or intentional errant behaviors can create inaccuracies. Adaptive systems should always be designed with a healthy skepticism around learner mastery data and should incorporate ways to verify and mitigate bad estimates. Some ways to guard against inaccurate mastery models include via instructor inputs, learner-choice recommendations that override system behaviors, and open learner models that let learners view (and sometimes directly or indirectly change) their mastery estimates.

In addition to mastery, many individual states and traits impact learning and, thus, can be useful targets of analysis. Learner states are malleable features that change from moment to moment, while learner traits are more fixed and change only over longer periods of time, if at all. Affective states, such as frustration or boredom, can reduce individuals' motivation to learn; physiological states, such as hunger or lack of sleep can also affect learning, both by impacting emotions and by moderating cognitive functions. As mentioned earlier, personality traits (e.g., goal orientation and general self-efficacy) can also provide some insights; additionally, personal characteristics, such as social identity traits or learning goals, may be useful.

Finally, aggregations of data from many learners over time can inform trend analyses or, at sufficient scale, be used to train machine-learning algorithms that uncover hidden patterns. At a minimum, collective data can provide some

general benchmarks, such as average completion time requirements. In more sophisticated systems, these data can also improve automated diagnoses and adaptation recommendations as well as inform system-wide improvements, such as identifying problematic sections in the instruction, optimum learning trajectories for different types of learners, and ways to incrementally improve the learning interface, content, or delivery.

> I want to be in a position where there's truly personalized learning based on a student's individual needs while at the same time balancing it with content-standard expectations. I'd love to see opportunities for students to dig in deeper, to have responsive educational opportunities.
>
> **Nathan Oakley, Ph.D.**
> Chief Academic Officer
> Mississippi Department of Education

Adaptations

The next important consideration concerns the kinds of adaptation the system will make. This could involve modifications to many factors, including display elements, what and when content is presented, the task sequence, the contents of instructional materials, embedded content features (e.g., selection of relevant examples), extrinsic content features (e.g., feedback and hints), instructional strategies and tactics, delivery methods, delivery devices, performance standards, learner goals, and various other interactions. These forms of adaptation can be expressed, to a greater or lesser extent, at the micro-, macro-, and meta-levels.

First, the micro-level focuses on task-specific adaptation in response to learner actions within a learning session, problem-solving opportunity, or single task. This could be, for example, in the context of one algebra problem or within a simulation scenario. Intelligent tutoring systems produce this sort of adaptation, albeit usually for fairly constrained purposes and subject areas. Intelligent tutoring technologies are becoming commodities, and it's easy to find commercial and open-source options with an internet search. However, many of these off-the-shelf tools work best in well-defined subject domains; so, while there are several available mathematics tutors, there are fewer for writing and fewer still for social and emotional skills. For ill-defined domains or specialized material, developing task-specific personalization can be a time-consuming effort, requiring extensive inputs from learning, engineering, and subject-matter experts. In those cases, the need for human expertise creates a bottleneck to their development[11] and is part of the greater cost of personalized learning.

Second, the macro-level focuses on content-wide adaptation. This could involve choosing the next instructional topic, sequencing instructional blocks within a curriculum, asking learners to repeat unmastered concepts, or allowing them to skip previously learned areas. The granularity of a given "topic" or "block" can vary widely, but they're meant to refer to learning episodes (rather than their component tasks or larger aggregates). Macro- and micro-level adaptation typically occur within a bounded system, that is, within a single application.

A third type of personalization is emerging at the meta-level. Meta-adaptation is applied across disparate curricula, learning systems, and/or organizational functions. In contrast to the micro- and macro-levels, adaptation at the meta-level occurs in system-of-systems environments. Meta-adaptation may involve, for instance, choosing which application to use to meet a particular learning goal—e.g., whether to train a medic on a new procedure via an online simulation, in a blended-learning workshop, or with an on-site mobile training

“

In education, we typically focus on supply rather than demand, compliance rather than growth, academic facts rather than context and experience. We’re trying to shift this. And we’re doing it in such a way to align our workforce, K-12, and post-secondary sectors. We need different pathways because kids are different. So, their journeys through our system should also be different.

Ken Wagner, Ph.D.
Education Commissioner
Rhode Island Department of Education

team. As this example highlights, different learning systems use distinct, and often complementary, approaches.[12] Intuitively, each experience might work better (or worse) for each learner. Consider, for instance, how professional development goals, workshop scheduling logistics, available technologies, urgency of earning the licensure, and risk tolerance of the organization might affect the way the hypothetical medic is trained.

Meta-adaptation could also augment learning activities within a given system. Imagine that the imaginary medic is learning that new procedure through a simulation, and the system diagnoses a gap in an interrelated area, say, pharmacology, that's not explicitly addressed by the current system. In this case, the meta-adaptive solution may be able to recommend external remediation resources, such as a book chapter, micro-learning refresher, or online course.

Meta-adaptation is a property of modern learning ecosystems, which combine multiple learning systems to let them share data and work together. This highlights one reason why it's important to use standardized protocols, machine-readable data, and well-defined metadata in learning systems. When data are shared across systems in standardized ways, it enables the personalization of unified and optimal learning paths [13]—at the broader, lifelong learning scale.

Technological Considerations

The design, deployment, and impact of personalization are heavily influenced by the technical environment where the system is deployed. This section highlights a sample of those considerations.

HARDWARE AND SOFTWARE

Computer-based personalization clearly requires hardware and software. Less obviously, these systems may require specialized components, for example,

extensive and highly secured digital storage for massive amounts of learner data, flexible servers capable of processing online AI algorithms at scale, or federated systems that share data across APIs. Similarly, depending upon the selected data sources, unique hardware devices may be required, such as wearable sensors, environmental beacons, or instructor input tablets.

BANDWIDTH

Although personalized-learning technologies can function natively on a client application, we imagine most systems will use networked components (and, likely, software as a service or SaaS solutions). However, bandwidth limitations may affect some deployments. For example, K–12 schools may need to share a limited internet connection across many users, or military units afloat or in austere conditions might have long periods without connectivity. In such cases, personalized-learning applications should be designed to reduce network usage, function despite slow response times, or operate without a connection. Methods for implementing this include batch processing, local replication, and caching of expected next steps when possible.

DATA

Personalized learning requires data.

Data models can be informed by extant data, whether collected through large-scale validation and norming studies, from other applications in a learning ecosystem, or from centralized data repositories. A word of caution, however: More isn't always better. It's important to judge the extent to which previously collected data accurately reflects the current population. In precision settings, for example, bias has been detected from differences as subtle as the order of questions within a test.[14] As this highlights, data quality is a key concern—whether data come from external sources or from system-collected inputs. Resilience to error, completeness, objectivity, fairness, timeliness, and consistency (to name a few) are all critical factors for personalization.[15]

Another key consideration involves storage and processing requirements. Some algorithms require data from hundreds or thousands of learners to calibrate a system before it becomes useful. Furthermore, depending on the algorithms, the amount of data generated could dramatically increase memory and computational requirements.

MACHINE LEARNING

Data, at large scales, can be used to train machine-learning algorithms. These can, for example, predict which learning paths will work best for different types of learners or create a self-improving system that detects obsolete content based on usage patterns.[16] Furthermore, machine learning can automate how personalization works for different populations or uncover changing interaction patterns over time. However, machine learning is not a silver bullet. It also requires a significant amount of data, which means many learners will need to use a system before a machine-learning algorithm is ready to fully deploy. Furthermore, many organizations will require ongoing validation of personalized-learning interventions, which may involve human oversight of an algorithm's functionality, leading to increased complexity and costs. Machine-learning can also suffer from transparency and explainability limitations.

TRANSPARENCY AND EXPLAINABILITY

Personalized learning systems should function transparently, that is, in a way that allows stakeholders to the see the data, analyses, and reasons for actions. Transparency is defined in contrast to black-box technical systems, which might perform the same actions but without a way for users to trace the system's decision processes. Ideally, outputs from personalization should be available at individual and aggregated levels, and they should allow users to drill-down (or drill-through) to reach explanatory detailed views. Data visualizations and dashboards designed for learners, instructors, administrators, supervisors, and/or commanders may prove useful here.

I think it's an interesting and exciting future, if there are multiple paths of developing competencies and ultimately getting the job you want. For way too long, we've had this single path to get to success. It's often served more as a filter than as a capability-building mechanism.

Shantanu Sinha
Director, Product Management, Google; Former Founding President and Chief Operations Officer, Khan Academy

Ideally, personalized learning systems should be explainable as well as transparent; this helps stakeholders understand the system's actions in order to properly evaluate and accept them.[17] Consider this distinction: A technical system that lacks transparency might contain proprietary functions and black-box machine learning; however, opening a window onto these algorithms won't necessarily make their underlying logic or emergent behaviors understandable. Transparency without consideration for end-user explanations can still create confusion; hence, personalized-learning systems also provide explanations of the reasons for their estimates and adaptations. As one example, a personalized-learning system may use probabilistic math to update estimates and combine them into decisions. Studies show that merely displaying probabilities isn't useful, because even well-educated users may struggle to intu-

itively understand them. Instead, explainable systems might provide natural language descriptions and evidence for their decisions in familiar terminology. Recent research is also investigating how to construct explanations after the fact for those complex systems that don't normally explain themselves.[18]

The output of transparent and explainable systems should be actionable for the end-users. Systems shouldn't simply output data; they should help make data meaningful to the stakeholders who use it—e.g., as open learner models, instructor dashboards, or visualizations designed for administrators and organizational decision-makers.[19] And when these systems incorporate good explainability, users are more likely to trust them, understand their limitations, take actions in response to system recommendations, and continue using the systems over time.

CONTROL

Transparent and explainable systems let users see why and how an application works, but what if those stakeholders want to control some of its functions? Systems can allow learners, instructors, and other human stakeholders to influence their estimations and/or actions. This sort of human-machine teaming is an ongoing area of research.[20] Ideally, learning stakeholders should be able to retain the kinds of control they want while they offload tasks to complementary technology that augments them with faster processing of large or detailed data.[21]

USABILITY

Finally, to effectively implement personalized learning, usability and user acceptance are critical performance metrics. Usability stakeholders include not only learners, instructors, and administrators, but also the instructional designers who plan and implement personalized learning, system engineers who need to monitor data models and adaptation algorithms, and even developers of other applications within a learning ecosystem.

BUILDING EFFECTIVE PERSONALIZED LEARNING

Ultimately, the purpose of personalization is to help individuals achieve learning objectives more effectively and efficiently. But how do we determine how well a particular system—its data, analyses, and adaptive interventions—performs? The first question to ask is whether a system is *functional*, i.e., does it give different learners experiences that fit their needs? Can we verify that it performs as designed and expected? It's useful to break these evaluation factors down into several categories. For instance, how does the system—as a software application—perform? Consider elements such as: the amount of work done by a user without help from the system, time-related information about the work processes, information related to the accuracy of underlying models, and the behavior of users in interacting with the system. It's also useful to evaluate the content within the application, for instance the extent to which a system produces recommendations for every possible target learning outcome, quality of the instructional "catalog" the system draws from, and quality of instructional interventions made.

The quality of instructional interventions can be measured in many dimensions, including the breadth, sensitivity, and completeness of different learning interventions, the number of unique recommendations the system makes in proportion to the entire catalog, or how often the system recommends the same few popular results to different users. Relatedly, questions to ask include: What were the differences in support and feedback between learners? What was the difference in the order of progression from one topic to the next? Did students get stuck at any point during task- and content-specific operations and, if so, where? How often did trainees drop out of training or pause it? Were there indicators of off-task behaviors or attempts to game the system?

The next question to ask is whether the system is *effective*, i.e., does it make adaptations that enhance the outcomes of the learning experience? Can we validate that it achieves the broader outcomes we're seeking? Most obviously, these may include training effectiveness and efficiency measures, i.e., did the system produce better topic mastery or faster speeds of completion versus other methods? More than that, other outcomes may be equally desirable, such as increasing retention rates, improving motivation, fostering certain attitudes, or encouraging social interactions.

Finally, there are *practical considerations* for evaluating a personalized learning system: What does it cost? How much time and how many resources were needed to develop it, and what are the costs of its operation and maintenance? Are the components of the system modular, scalable, extensible, and reusable? How much data does it collect, and how are those data handled? And, ultimately, is the system providing good return on investment.

CONCLUSION

Personalization is among the most important ways to achieve effective learning outcomes, and computer-assisted personalization can bring this benefit to more learners. The field of learning science has advanced our understanding of what and how to adapt learning (through decades of research in educational theory and cognitive science), and innovations in technology are improving our ability to implement these methods, efficiently and effectively at scale.

The promise of personalizing learning will be realized when individual components and learning systems work together, as a system-of-systems, sharing data and optimizing learner trajectories across longitudinal and diverse experiences. The potential for learning personalization is immense, and researchers and educators are just beginning to explore the possibilities.

One of the most important points we heard…is the need for a list of principles—and that technology shouldn't lead. It should be about technology enabling our systems to attain equitable and ethical outcomes.

Amber Garrison Duncan, Ph.D.
Strategy Director, Lumina Foundation

Learning Science

> If we can assess both formal and informal learning experiences in our students, what might you use that data to inform? Teamwork skills? Classroom management? Extracurricular skills? As a teacher, I have little control over the design of statewide summative assessments, but I could put those skills and others, like thinking and problem-solving, at the forefront. Developing these skills is also an objective. Students are always aware that they’re honing a number of skills that will help them be successful outside of our class.

Kimberly Eckert

Teacher, Brusly High School; Louisiana State Teacher of the Year 2018

CHAPTER 11

ASSESSMENT AND FEEDBACK

Debra Abbott, Ph.D.[1]

The future learning ecosystem will change the management and processing of learners' data across systems, communities, and time. As new analytics capabilities evolve, they will catalyze change in several ways: by increasing the level of insight into how learners develop over longer periods of time, by enhancing the ability of instructors to make teaching more responsive and adaptive, and by recommending experiences and learning pathways designed to meet the needs of individuals. However, new technologies won't enhance learning if they're applied without purpose. The current system too often elicits an abundance of learner performance data without making effective use of it. And, too often, other factors essential to learning—such as motivation and long-term goals—are ignored, or learners receive feedback that's neither useful or actionable and, hence, quickly forgotten. This chapter lays out an updated framework for assessment and simultaneously emphasizes the importance of analyzing the intent behind assessment activities, reforms available through improvement of formative feedback, and affordances required in a technology-enabled system of assessment.

Background and the Limits of Current Practice

As technology rapidly transforms training and education, the choices regarding learning assessment have become more confusing for instructors and riskier for education and training program managers, who must navigate a

> We need **formative** rather than just **summative** assessments; we need to push and melt these technology tools to do a better job and use the analytics in linear or nodal fashion. The goal is to understand individual aspects for education that ultimately enable us to give them a better education than they've ever had.

Keith Osburn, Ed.D.
Associate Superintendent, Georgia Virtual Learning
Georgia Department of Education

bewildering forest of accountability-oriented data on programs, classrooms, and outcomes. Unfortunately, such recordkeeping often takes on a life of its own as data, originally connected to specific learning goals, becomes an enterprise asset to be gathered, maintained, and reported for its own sake. Additionally, developments in research, paradigm shifts in assessment, and changes in the landscape of learning have essentially rewritten the rules of the game. The professional development of education and training stakeholders, however, has not kept pace with these changes, and this has frequently led teachers, instructional designers, and others to operate under outdated models of assessment—where assessments are primarily summative, quantitative, and focused on decontextualized snapshots of learner performance.

Valerie Shute and Matthew Ventura sum up the consequences of this state of affairs:

> Many of today's classroom assessments don't support deep learning or the acquisition of complex competencies. Current classroom assessments (referred to as "assessments of learning") are typically designed to judge a student (or group of students) at a single point in time, without providing diagnostic support to students or diagnostic information to teachers.[2]

Often, instead of providing a clear path towards a solution, the advance of technologies—including algorithms that personalize learning, new delivery platforms, and a host of other rapidly expanding choices—muddy the waters. There's a risk that novelty effects or the complexity of some learning technologies mask flaws in design. Learning science informed by research-based principles can help. Whether learning takes place in virtual reality or a classroom seminar, the history, principles, and processes of learning science constitute a valuable toolkit for learning ecosystem designers and developers.

PRECONDITIONS FOR ASSESSMENT: THE ESSENTIALS

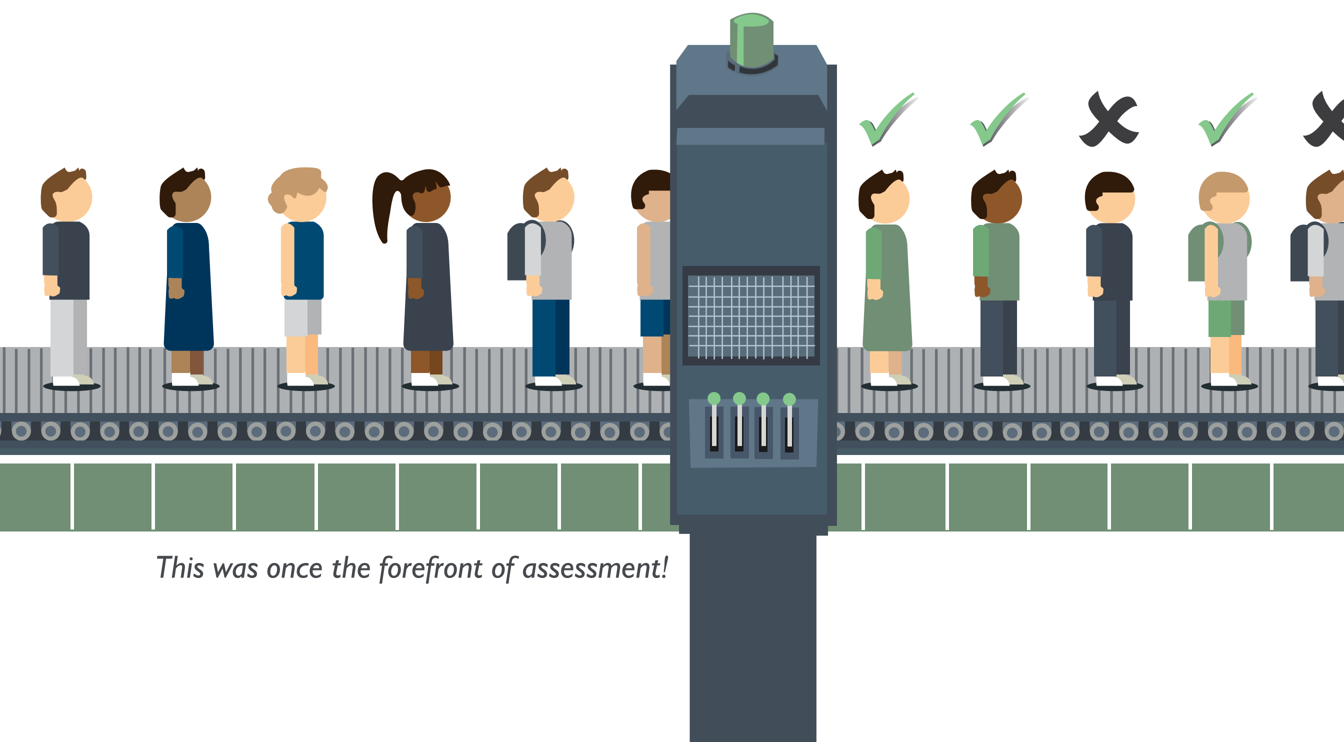
In *Visible Learning*, John Hattie names two elements as "essential to learning": (1) a challenge for the learner and (2) feedback.[3] Similarly, both factors serve as a foundation, or as the minimum requirements for, assessment. If challenge is insufficient, neural connections are neither strengthened nor altered in a learner's brain, and if useful feedback isn't present, the learner is acting blindly, unable to relate her performance to either current or future learning goals.

New-age learning analytics have moved the needle considerably as they allow for continuous, real-time monitoring of performance and can present up-to-date dashboards to stakeholders. This is a far cry from assessment in the age of our grandparents. For most of the 20th century, a "factory model" of training and education prevailed and, with it, an assumption that teaching is a transmission process, with learners on the receiving end. The goal was to fill everyone's head with knowledge and deliver a uniform product, the graduated student, to society. Instructors were told that a period of teaching needed to be followed by an assessment, followed by another period of teaching and another assessment, *ad infinitum* until a program of instruction ended. Assessment

was thought to be an on-again-off-again occurrence situated in this linear process.

Many decades ago, the design of assessments wasn't considered particularly important, since they were like accessory events to the primary focus of teaching and learning. Paper-based activities such as tests and essays prevailed—except in special settings, such as art, speech, or physical education where performance mattered. And in this environment, it was assumed that students could receive feedback in the same manner as they did any other sort of information: Many instructors never thought twice about red-inking students' papers or telling them harshly that they lacked writing or thinking aptitudes—a practice that would lead some learners to a state of learned-helplessness. Conversely, it was acceptable to praise high-performing students' abilities and intellect, often undermining their growth mindsets and instilling a false sense of the level of effort required to learn.

Nowadays, most classrooms, whether they exist within in a company, at a military base, or on a computer screen, experience at least some differences in assessment practice and the attitudes toward it. Assessment state-of-the-art



This was once the forefront of assessment!

in many places can be described (albeit cautiously) as more learner-centered than in the past. These changes may be ascribed to the impact of constructivist learning theories and methods such as active-learning and learner-centered design. Improved practices and attitudes have also resulted from numerous assessment movements that have achieved notice, if not popularity, over the last few decades: authentic assessment, performance assessment, alternative assessment, formative assessment, portfolio assessment, embedded formative assessment, longitudinal assessment, and assessment *for* learning (which is distinct from assessment *of* learning).

So, in this new age must we always be assessing? What's best for learners? For now as well as in the foreseeable future, some forms of student work and performance will be prioritized above others as the significance of any given assessment is socially constructed. For example, in adult education, assessments that mirror authentic types of workplace tasks may be more greatly valued and better serve to articulate learning objectives. It's important to recognize that not all actions or learning artifacts individuals produce will have equal value relative to learning goals, program objectives, or learning outcomes. Part of the challenge, therefore, lies not only in designing and delivering effective assessments but also in prioritizing their applications and in considering their broader roles within the learning ecosystem.

Building upon the progress made to date, assessment in the future must continue to empower education and training stakeholders. Understanding assessment is no small feat, but to start, it's useful to clarify the true purpose for systems of assessment, including for singular high-stakes assessments, and to encourage a mindset shift away from 20th century preconceptions that couple valid measurement almost exclusively with summative measures such as tests, papers, quizzes, and the like. It's also useful to become versed in developments arising from research in formative assessment, as well as its close cousin, feedback—which has a symbiotic relationship with learning. Finally, as we embrace a more technology-centric approach to learning, it's useful

to consider the affordances that learners will require in environments where assessment may occur in real-time and continuously.

Purpose of Assessment

The ostensible reason for assessing learning is to aid decision-making. However, assessments are quite often used to hold an entity or a person accountable for meeting predefined criteria or achieving certain outcomes. As such, student learning outcomes are almost always written to reflect some level of desired change, such as the desire for increased performance on a standardized test; advancement in subject-area ability; or achievement of a curriculum objective defined by a certification entity, a state-level department of education, or an employer. In a classroom, quizzes may be used to hold students accountable for studying; at an organizational-level, standardized tests may hold school districts accountable for collective performance, and in workforce contexts, assessments might be used to assign accountability for adhering to regulations by verifying employees have completed compliance training.

However, despite their practical utility, these sorts of accountability assessments *of* learning often have less utility *for* learning. Susan Hatfield, in Kansas State University's long-running practitioner paper-series on improving learning in higher education, highlighted the distinction:

> The best way to determine the reason for doing the assessment is by examining the focus of the plan. Is the focus simply on collecting data? Or is the focus on using data to improve student learning? Assessment plans designed to appease others generally involve a lot of data collection but are rarely put to meaningful use. Plans that focus on student learning connect collected data to potential courses of action.[4]

The potential "courses of action" Hatfield mentions might occur at various conceptual levels, from more immediate task- or course-focused perspectives to organizational and lifelong learning considerations. In other words, whether

Recently I took a test for Google for Education Certification. I thought it would be a typical test so I crammed… how I always tested. That's usually how you have to prepare for nearly every standardized test I've ever taken. However, when I started the test I realized it's not a crammable test! It's all practice based so I actually learned while I took it. I had all the tools, it felt like fun, and most of all it was meaningful. I hold this experience dearly!

When I took the Level 2 test in the series, I didn't prepare the same way! I looked at problems and thought through scenarios. I didn't even realize the hours passing in the test. I wasn't bogged down. From then, I pushed myself to start assessing my students in the same way.

Authenticity is the key. We're stuck in a century that's long gone. We need to let go of that and start encouraging the sort of growth mindset that allows students to perform and grow and struggle with dignity. This is how they'll feel prepared for life. The school of life… it's all competency based.

Kimberly Eckert
Teacher, Brusly High School
Louisiana State Teacher of the Year 2018

used for accountability or formative learning, assessments that inform *macro*-level decisions should (and generally do) differ from those at *micro*-levels. Macro-level decisions rarely, if ever, are based on a single source of the evidence. In an education system, for example, the higher one goes up the decision-making tree from classroom, to school, to district, to state, the more important it becomes to aggregate the results from multiple, varied assessments and make a thoughtful human judgment called an evaluation. Evaluation is a complex art, dependent upon accurate data and a capacity for judgment derived from knowledgeable instructional practice. Experience with effective assessment and instruction is, in fact, the crucible that enables individuals to make good evaluative judgments.

As evaluation enters the picture, it widens the aperture about the purpose and utility of assessments. Evaluations and other macro-level assessments should emphasize measures of effectiveness, that is, meaningful outcomes in terms of the impact of learning, such as college admittance rates or improvement in job performance. Measures of effectiveness are contrasted against measures of performance, or process-focused measures such as a student's grade-point average or how many people completed a training workshop.

This distinction gets to the heart of training and education. Whether individuals are enrolled in a high school composition course, corporate training program, or professional military education seminar, the aim of most formal and informal learning is to engender practical competence—competence that's necessarily instantiated in a particular context or environment. For example, if you tell students to achieve a set of general communication outcomes, they're likely to shrug and disengage. However, if you focus those students on writing their college entrance essays, corporate work plans, or five-paragraph field orders, they're not only likely to show greater motivation but assessments of their abilities are apt to be more authentic, meaningful, and reliable.

One of the most persistent problems in (adult) training and education stems from inadequate understanding of how applied performance—real people

performing real jobs—relates to learning outcomes. Part of the challenge lies in understanding the distinctions among competence, competencies, and learning outcomes. Competence is a hidden property, inherent to a person, team, or organization. It can't be directly assessed. Competencies, on the other hand, are the clusters of knowledge, skills, attitudes, attributes, and other characteristics that attempt to itemize competence. In turn, these competency descriptions can be used to articulate job requirements or to inform learning outcomes for training and education. (See Chapter 13 for more details on competency-based learning.)

Unfortunately, the more a certain activity requires higher-order cognitive and social-emotional competence, such as intrapersonal communication or leadership skills, the more difficult its components are to identify, define, and assess. Similarly, practical competence requires the interplay of different competencies (such as empathy and communication skills combined with subject-matter expertise), which also creates difficulty. This is the classic "iceberg problem." For example, capabilities your boss thinks are important for your job are anchored to its most visible aspects, while you know that your job also involves another set of less visible, less well-defined facets. The same is true outside of an employment context; those capabilities that prepare someone for life, or to be a good member of our society, are problematic to characterize, delineate, and measure.

In summary, having a clear view of the purpose of an assessment is the first step towards increasing its productive utility. The true purpose should be analyzed: Is the desire to measure the most meaningful, or merely the most convenient, things? Has the system of assessment sufficiently addressed real-world competencies, and are the assessments of sufficient breadth and depth to realistically measure them? Finally, what evidence is there that assessment results are being used to improve instruction? To the latter question, the results from assessments can inform instructional adaptations or organizational decisions,

and in particular, they can be used to generate valuable feedback to learners, teachers, trainers, and organizations.

WHAT LEARNERS NEED FROM ASSESSMENTS

By their very existence, assessments affect learning. Individuals will change their behaviors if they know they'll be tested, and completing an assessment encourages learners to recall and exercise their knowledge and skills. However, substantially more value comes from actually using the evidence collected from an assessment. Unfortunately, all too often reams of data are produced without any practical application of them.

1. Serviceable Feedback

The importance of feedback to assessment is vastly underrated, and what constitutes high-quality feedback is often misunderstood. At the most foundational level, quality feedback should enable an instructional system to close the loop—to come full-circle—while simultaneously affording learners and organizations data that improves their development processes. Royce Sadler observed in his widely cited article on formative assessment:

> If the information is simply recorded, passed to a third party who lacks either the knowledge or the power to change the outcome, or is too deeply coded (for example, as a summary grade given by the teacher) to lead to appropriate action, the control loop cannot be closed and "dangling data" substitute for effective feedback.[5]

The "control loop" in Sadler's quotation concerns the system-control function, which conceptualizes learning as a loop and feedback as an intervention

used to iteratively close the gap between the actual level and desired level of a particular capacity. Assessment results that don't meaningfully inform some aspect of teaching and learning, or that fail to help this progression, are consider "dangling data."

The term "feedback" is not only vague but itself a misnomer. Assessment expert Dylan Wiliam is fond of saying that it more aptly refers to the view from the front windshield rather than the rearview. It can refer to performance observations or advice, reflective prompts and questions, or other information relevant to an individual or group; and it may refer to past, present, or future performance.

So, as long as teachers and trainers deliver accurate and relevant feedback, what's the difficulty? It was Sadler[6] who again uncovered the key: There are several reasons a learner may have trouble implementing feedback—even if it's of exemplary quality and delivered early enough in a period of instruction to be useful. First, the line may be blurry for the learner between the work as realized and what was intended; individuals may see potential where instructors may see flawed work. Second, terminology or criteria related to the instructional task may not be understood. Third, students may fail to grasp tacit knowledge. For example, statements such as "this doesn't follow logically from what goes before" makes no sense to students who don't recognize the hallmarks of subpar writing structure: It looks fine to them. Last, learners often cannot consolidate or apply advice fast enough for learning to stick. To be effective providers of feedback, then, teachers and trainers need to better understand learners' own visions of their work, their challenges, and any gaps in their learning. Also, learning facilitators would be wise to implement learner self-assessments and peer assessment, since both can go a long way toward meeting these needs.

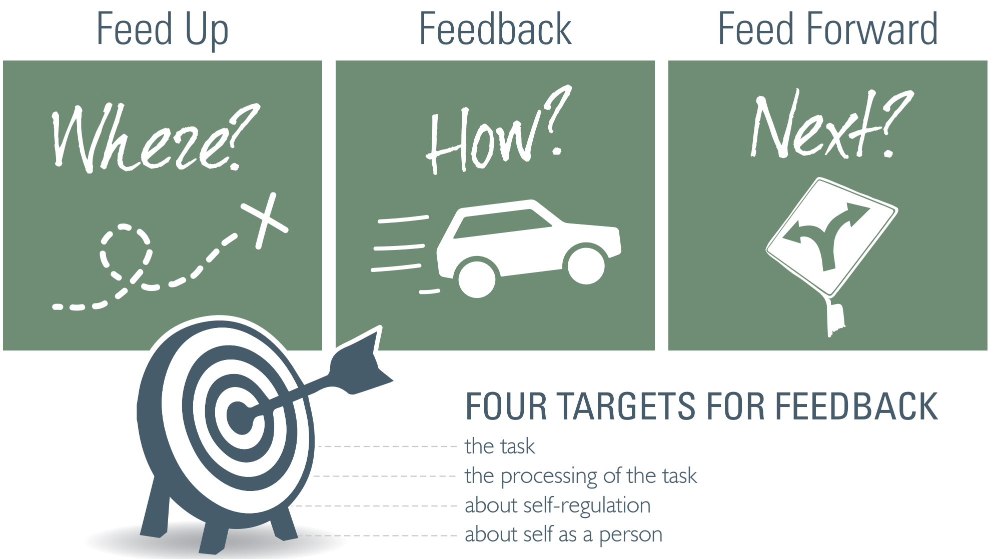
Another model for the creation of more comprehensive and appropriate feedback comes from the work of John Hattie and Helen Timperley.[7] They believe that learners need three questions to be answered concerning their perfor-

mance. First, they need information about the performance goal, which answers the question, "Where am I going?" This includes specific and comprehensible success criteria and is referred to as the "feed up" stage. It's followed by the "feedback" stage, which answers the question, "How am I going?" Lastly, the question is, "Where to next?" This final stage is called "feed forward," and it's probably the most critical juncture for applied learning and development. Hattie and Timperley also identify four targets for feedback: feedback about the task, about the processing of the task, about self-regulation, and about the self as a person. Their three questions apply to each of these categories, and together these twelve targets become a useful, heuristic catalog for learner feedback.

2. Evidence-Based Systems

As the characteristics of training and education evolve, enabled by the affordances of the future learning ecosystem concept, new models of assessment and feedback can be more readily supported. For example, the proliferation of new media devices, wearable sensors, and IoT appliances has correspondingly created an abundance of data. Even without these new hardware tools, someone's activities (say, in a social-media app or on an e-commerce site) can be tracked with uncanny precision. By analyzing an individual's behaviors, as revealed by these data, we can start to better understand their attitudes and capabilities in ways unimaginable with legacy assessments.

Valerie Shute and colleagues popularized the concept of "stealth assessment," which involves interweaving assessments, informed by evidence-centered design principles, directly and invisibly into the fabric of an application environment. For instance, they integrated stealth assessment into a popular video game (*Plants vs. Zombies 2*), and from player interactions could infer measures of their problem-solving skills. Shute et al. have recommended this approach for applied, competency-based assessments, particularly for certain



ill-defined capabilities otherwise difficult to evaluate, such as persistence, creativity, self-efficacy, openness, and teamwork.[8]

Shute and her colleagues advise against hiding assessments or evaluating individuals without their awareness; rather the term "stealth" refers to the frictionless integration of the measurement, where it's inherently situated within a task rather than an exogenous activity to it. Two other characteristics of stealth assessment are that it's continuous (in contrast to single-point summative testing) and probabilistic (in contrast to the predefined criteria frequently used by standardized exams with well-defined correct and incorrect answers).

Stealth assessment can be supported by, or otherwise inform, various data-driven analysis methods. As discussed in Chapter 9 of this volume, learning analytics and educational data mining are two such approaches. Stanford University Professor Candace Thille has drawn parallels to the way similar technologies have transformed e-commerce: Companies can predict buying patterns, use targeted advertising, and employ frequent A/B testing to continuously improve their businesses. Analogous capabilities are being applied to

learning to uncover learner needs by group or type, help personalize learning based on individual needs and characteristics, or help predict which individuals are likely to succeed in a given course.[9]

> *"The big power of this technology is that we can construct these interactions, collect this data on students' interactions, and use it to drive very powerful feedback loops in the learning system." – Candace Thille*[10]

However, stealth assessment, learning analytics, and educational data-mining can suffer from the "dangling data" problem that Sadler mentioned. In other words, it's possible to estimate someone's problem-solving ability, let's say, without taking steps to support its improvement or even communicating the evaluation results to the learner. Ideally, such data shouldn't merely be used to pass external judgment—the results should be put to work, helping individuals and organizations better meet their goals. Further, this doesn't just mean using the data to inform automated personalization or AI-based adaptation.

With the growing use of automation, we run the risk of disempowering learners, teachers, and trainers. Despite their enormous potential, automated systems are only as strong as their weakest link—which is very often the user interface and user experience. Even today, in arguably simpler times, computer-assisted instruction is fraught with UI/UX design challenges, delivery tool mismatches, and assessments that learners perceive as irrelevant. While new technologies can enable more frequent and better attuned assessments, these may be relatively meaningless if they fail to offer learners and instructors sufficient interaction affordances, such as for understanding and making use of the assessments, feedback, and subsequent intervention recommendations.

3. Learner Autonomy

Professor Jon Dron, from Athabasca University, posited a theory of trans-

actional control, which may be relevant, here. It builds on Michael Moore's well-known theory of transactional distance, which essentially shows that the relative "distance" someone feels in an e-learning context is based on the amount of interaction and structure in it, rather than the physical separation between learners and instructors.

Dron extended the transactional distance theory to highlight the impact that control, or the extent to which choices are made by teachers and learners, is the fundamental dynamic of it. The central idea is that flexibility, negotiation of control (or "dialogue"), and autonomy all matter a great deal in learning contexts.[11] The solution isn't as simple as giving learners (or instructors) full autonomy; rather, a thoughtful approach, considerate of control, is needed. As Dron explains:

> Most learning transactions tend towards control by either the learner or, more often, the teacher. From a learner perspective, being given control without the power to utilize it effectively is bad: learners are by definition not sufficiently knowledgeable to be able to make effective decisions about at least some aspects of their learning trajectory. On the other hand, too much teacher control will lead to poorly tailored learning experiences and the learner may experience boredom, demotivation, or confusion. Dialogue is usually the best solution to the problem, enabling a constant negotiation of control so that a learner's needs are satisfied... The ideal would be to allow the learner to choose whether and when to delegate control at any point in a learning transaction.[12]

A key takeaway is that learners must be afforded enough autonomy to remain engaged, construct their own knowledge and skills, and develop their self-regulation abilities. Striking the right balance between teacher-controlled—or AI-controlled—learning versus learner-regulated anarchy is key. As Dron's quotation highlights, systems that favor negotiated control, as much as possible, are preferred. In the future learning ecosystem, this prompts us to consider how control is distributed across individual and collective learners, teachers, *and* automated systems.

RECOMMENDATIONS

Given the principles of assessment and feedback, as well as the opportunities (and challenges) afforded by new technologies, there are several precepts to consider regarding assessment and feedback for the future.

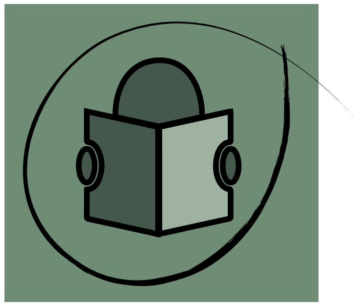
1. FIRST AND FOREMOST, CULTIVATE LEARNER MOTIVATION. As long as designers of instruction strive to cultivate learners' interest and motivation with regard to assessment activities, then they are excellent change agents.[13] When designed and implemented well, assessments afford rich opportunities to develop learners' concepts, communication skills, subject-area expertise, judgments, and abilities.

2. MAKE ASSESSMENT AND FEEDBACK LEARNER-CENTERED. Learners aren't merely passive vessels but active participants who seek out useful feedback when motivated to do so.[14] Educators and trainers must try to view assessment through their eyes. Success in assessment is tied to learner engagement (like everything else in education and training). Even in an imaginary future, where AI systems have the ability to determine learning priorities, content, and sequence, learners will still need to be actively engaged, given explicit feedback, and afforded agency over their own learning.

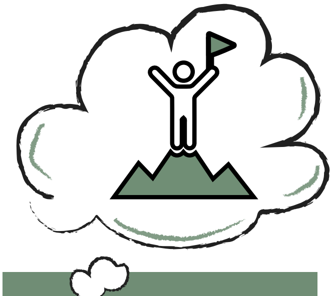
3. INTERWEAVE ASSESSMENTS THROUGH INSTRUCTION. Instruction and assessment have a truly symbiotic relationship; they're inextricably linked and interactive.[15] A variety of types of assessment activities should be threaded throughout lessons, modules, and courses of instruction. Even so, assessments will always vary in terms of their relative importance, and this is as it should be: The extent to which an assessment fulfills the overarching objective of instruction represents the degree to which it possesses socially constructed *value*.

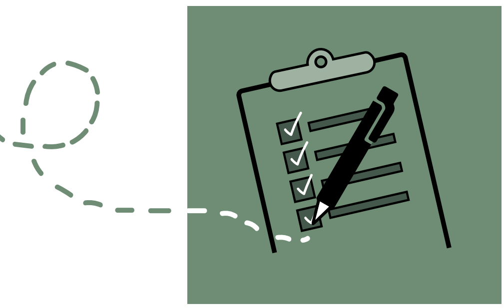
Assessment and Feedback Recommendations

1. Cultivate learner motivation



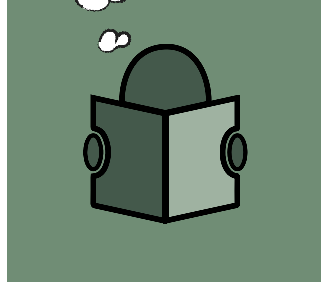
2. Make assessment and feedback learner-centered



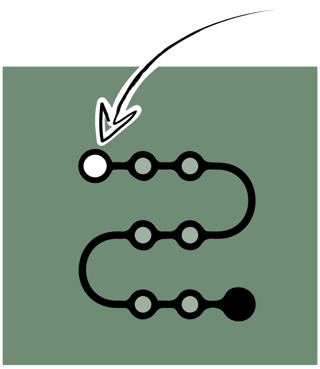


3. Interweave assessments through instruction

4. Vary the types of data collected

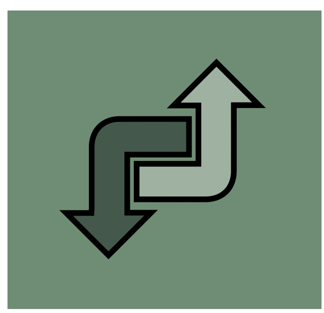


5. Mitigate the fluency illusion



6. Plan for curricular alignment early on

7. Integrate feedback into learning design



8. Plan for systemic change

Example

COMPUTERS AND HUMANS WORKING IN CONCERT: At Arizona State University, we have some huge introductory courses, for example, College Algebra with 3000 students. About 5 years ago, we created an adaptive general education structure. There are approximately 13 modules for College Algebra, but if students finish early, they can enroll in the stretch-version of the course—it doesn't cost and it gives them credit for the second semester. We use a program called ALEKS for instruction, adaptive testing, and adaptive placement to determine which courses each student is ready to take (Algebra, Precalculus, or Calculus). Sometimes ALEKS isn't perfect; so, perhaps someone ends up in College Algebra and they get through the course in the first month—that's fine! There's one more aspect of this, but it doesn't scale well: Students are also required to attend class, where they're coached by teaching assistants and take exams. Every week or so, they work in small groups with more difficult problems, and they're scored as a group because collaborative problem-solving is an important skill. During those days, it's active—*and the students are loud!*—but it helps keep the them engaged in the course. Note that these are undergraduates; so, the in-person courses also act as a bit of a clinically counseling apparatus. The assistants help mentor, and if they find struggling students, they can refer them to a counselor. We have a web-based system for the counseling staff, too. We're really into helping the first-time freshman!

Courtesy of Kurt VanLehn, Ph.D., Professor, Computing, Informatics, and Decision Systems Engineering, Arizona State University

4. VARY THE TYPES OF DATA COLLECTED. A functional system of assessment for learning should be eclectic and incorporate a variety of measures such as quantitative, qualitative, estimated, and predictive data types. This approach suits the social-science aspect of the measurement objective. Looking ahead, as the vision of an interconnected learning ecosystem comes to fruition, assessment evidence from highly varied sources can be collected,

stored in persistent learner profiles, and examined in aggregate. This will start to shed more light on competencies *in situ* as well as the interplay among diverse knowledge, skills, attitudes, and other characteristics.

5. MITIGATE THE FLUENCY ILLUSION. Today, our most highly valued assessments are usually summative performances (e.g., final exams, formal presentations, final projects, professional portfolios) that differ in significant ways from practice and study contexts. This discrepancy can create a "fluency illusion," where individuals misjudge their capabilities by thinking that their fluency—or ability to remember and apply skills—in practice settings will translate to performance scenarios. To mitigate this, learners require opportunities for practice assessments such as pre-tests or trial performances that are spaced out in time, occur in a mix of locations or under varying conditions, and are sequenced in a special way that mixes problems or content elements (referred to by educators and psychologists as "interleaved" practice).[16]

6. PLAN FOR CURRICULAR ALIGNMENT EARLY ON. Good assessment is planned for very early in the instructional design process, and it begins by imagining what post-instructional success looks like. Outcomes and assessments are like the "bones" of instruction and should be constructed first, so that lessons may be structured around them.[17] This process is referred to as the backwards design of assessment.[18] Relegating assessment to an ancillary concern typically puts validity at risk by increasing the likelihood of measuring achievements that are unrelated to the specific learning objective of interest.

7. INTEGRATE FEEDBACK INTO LEARNING DESIGN. As with assessment, feedback approaches should be incorporated early into the instructional design process. While feedback as a dialogue between instructors and learners is highly productive, learners can (and often do) obtain feedback from multiple sources. How these multidirectional and distributed feedback loops fit into the design of instruction requires planning.[19] Explicit and thoughtful efforts are needed, particularly as automation becomes more profuse, threatening to reduce individuals' control and transparency of learning. Good feedback de-

sign ensures that learners receive useful information that's timely, actionable, and customized to their needs.

8. PLAN FOR SYSTEMIC CHANGE. The most challenging aspect of assessment is often the sleuthing necessary to figure out how all the parts fit together: How do the instructional design, delivery, assessments, and measurement data collectively tell the story of what a learning experience was like for a group or individual, and how can we improve such experiences *systematically*? Organizationally, there should be a forcing function or mechanism that causes the results of assessments to be utilized. However, teachers and trainers, or automated systems, shouldn't make those decisions alone. Taking action in response to assessment is important, but equally critical is considering how to bring learners into that equation.

Conclusion

It's strange that we don't hear more frequent comparisons made between the practice of teaching and the practice of medicine. Both require intense amounts of skill, professional development, and consistent practice. As assessment expert Dylan Wiliam says: Teachers need professional development because the job of teaching is so difficult, so complex, that one lifetime is not enough to master it.[20] Mastering assessment in teaching is a bit like mastering triage skills in the emergency room, in that successful intervention depends on successful evaluation of the unique situation of each individual. And, yes, because so much of our survival and future success depends on acquiring effective training and education, one's learning needs often are (at least in a theoretical sense) as urgent as many health needs. Perhaps because nearly all of us have been coaches, trainers to workplace apprentices, or teachers to our own children, the instructional process may have lost its mystique somewhere along the way. Hopefully, a clearer vision may help us appreciate the mystery, regain some enthusiasm, and redefine as well as reimagine assessments to work more effectively and purposefully to uplift and motivate our students.

CHAPTER 12

INSTRUCTIONAL STRATEGIES FOR THE FUTURE

Brenda Bannan, Ph.D., Nada Dabbagh, Ph.D., and J.J. Walcutt, Ph.D.

As education and training opportunities become ever more available—on demand, anywhere, anytime, and across our lifespans—individuals increasingly experience bursts and waves of disconnected, transitory, and episodic learning. Hence, it's our challenge, as learning science practitioners, to help learners filter data noise, focus on relevant information, and meaningfully connect new learning to past experiences. Towards that end, this chapter provides a framework that illustrates a shift in thinking about instructional strategies, refocusing these principles to better support the future learning ecosystem and foster connections across learners' lived experiences. Building on traditional instructional strategies shown to be effective in formal learning contexts, we propose new approaches that cut across individuals' learning episodes, potential careers, and lifespans.

Background

For decades, the design of instructional strategies (and learning systems, in general) has been largely treated as a micro-level, reductionistic, and linear activity—focused on analyzing particular learning outcomes, aligning them with suggested instructional strategies, and then delivering instruction in straightforward ways to elicit desired responses. However, today, learning occurs in a multidimensional frame, blending formal, nonformal, and informal experiences that transcend time, space, medium, and format. The complexity

of our lives and diversity of available technologies warrant a shift in learning theory, away from standalone learning episodes that push information in a singular manner and towards a multipoint, multimodal view where learning crosses the boundaries of time, context, delivery methods, and devices.

Although networked technologies have already made it possible to support ubiquitous lifelong learning, our teaching methods and instructional strategies haven't caught up with these new learning affordances. We're still designing at the module, course, or program-level, ignoring broader learning pathways, and discounting the additive peripheral events learners encounter throughout their lives. We need to modernize our conceptualization of "instructional strategies," and expand these principles to support a more open, flexible, and personalized learning ecosystem. We need to create continuous and meaningful lifelong learning and find ways to incorporate elements from diverse and informal contexts into it.

Fostering more cohesive, coherent learning will likely involve designing some manner of "macro-level instructional arcs" that span a mosaic of individual and collaborative learning experiences—meaningfully intersecting different events across a lifetime. It will also require us to make better use of multimodal communication tools to help individuals curate information and generate knowledge across experiences. This position reflects the connectivist view of learning, which perceives knowledge as a network, influenced and aided by socialization and technology.[1] From this standpoint, knowledge isn't only contained within an individual or information artifact; it's also distributed externally through networks of internet technologies and communities, accessible via social-communication tools. Learning takes place in these autonomous, diverse, open, interactive, collaborative, and global knowledge systems. Hence, recognizing relevant information patterns, constructing new connections, and nurturing and maintaining connections become critical skills for achievement. Individual learning opportunities can be (and have been) designed with this paradigm in mind;[2] the full solution, however, requires even more.

> "At IES [the Institute of Education Sciences within the U.S. Department of Education], we funded two R&D centers to bridge cognitive science and education.…This important work was especially useful in demonstrating what the research to-date has not addressed. When you take something that has been extensively researched in the lab setting—like self-explanations, making comparisons, or studying worked examples—and then implement those principles in the curriculum, there are a lot of design decisions need to be made: What kinds of comparisons need to be made? And how do you present these ideas on a textbook page? What information do you highlight and how do you highlight it in a textbook? In the lab, these types of questions don't come up. Another issue is, how do you combine learning principles like retrieval practice, worked examples, etc.? Historically, we've studied these principles in isolation, but when you combine them into a year-long learning experience, there are many questions about how to do that effectively.
>
> Erin Higgins, Ph.D.
> Program officer within the Institute of Education Sciences
> U.S. Department of Education

Limits of Conventional Instructional Design

Traditionally, an instructional designer begins with some given set of criteria such as the lesson's purpose and subject matter, learners' general characteristics, and likely some logistical constraints. From these, designers extrapolate the type (e.g., psychomotor, cognitive, affective) and level of learning outcomes (e.g., remembering and understanding, applying and understanding), objectives of the associated assessments (e.g., formative, summative), and other delivery factors (e.g., course schedule, perhaps). They break the goals into objectives, the objectives into tasks, and then select some set of instructional interventions to help learners master each component. They continue working in this linear fashion—breaking down the plans into smaller and smaller parts, and carefully considering the content, delivery, and learner activities for each. This is known as "backwards design."[3]

The traditional approach to designing instruction generally assumes a given target—a particular individual or cohort—as well as a specific setting and general set of conditions. It focuses on determining the appropriate configuration of instructional interventions in insular and finite curricular units, such as a course or training program. However, as we envision learning across lifetimes, this model no longer suffices. In the future, we need instructional design that encompasses diverse learning experiences, media, populations, and contexts—many of which will fall outside the instructional designer's purview. In other words, we need an updated approach that:

- Facilitates learning as a gestalt, derived from the collective sum of all learning events and experiences;
- Recognizes learning outcomes are increasingly self-directed and stitched across different contexts, networks, and communities; and
- Actively incorporates technology to enable learning—not only as an instructional delivery mechanism but also as the "glue" to connect learning events to one another.

Consequently, we need a multidimensional model of instructional design that integrates traditional micro-level interventions as well as macro-level principles, that considers not only instructor interventions but also learners' own agency, and that actively connects experiences across the crisscrossing landscape of learning.

Strategies and Tactics; Instruction and Learning

Instructional design terminology is used in a hodgepodge of ways.[4] We won't attempt to unkink it, but it's useful to highlight several terms. First, consider "instructional strategies" (also frequently called "teaching strategies"). This is the most common way to refer to the instructional interventions used by teachers, trainers, and instructional designers. In more careful discussions, this concept is typically divided into "instructional organizers," at a more

global level, and "instructional tactics" at a more granular one.[5] Exactly where the lines are drawn between these levels is a bit fuzzy—and largely irrelevant to our discussion. What's more applicable is the general idea that there are instructional design distinctions at different conceptual and granular levels.

The second important distinction comes in comparing *instructional strategies* to *learning strategies*. Where instructional strategies are devised and applied by learning experts to some planned block of instruction, learning strategies are personal methods used to improve one's own knowledge, skills, and experiences across the range of formal and informal learning. In theory, learning strategies and instructional strategies mirror each other. For example, an instructor might design a lecture, provide some illustrative examples, and give feedback. Meanwhile, a learner may work to memorize terms, mentally compare-and-contrast new ideas to prior knowledge, and reflect on performance.

In many ways, the distinction between instructional strategies and learning strategies is a question of *control*. As discussed in the previous chapter, transactional control (or the extent to which the learner makes decisions versus some external authority, such as the instructor or software) is an important factor. As one might expect, control of learning can be handled in different ways: Internally by the learner, externally by some structure or authority, or insufficiently, without effective support from either internal or external sources. Also, as Jon Dron's transitional control theory emphasizes, some form of negotiated control, in the middle of internal–external control continuum, is best.[6] Hence, the notable concept here is not only the contrast of instructional strategies to learning strategies, but also the potential for their integration—that is, blending learner-directed and authority-directed strategies together.

One final distinction for the future learning ecosystem is belied by its name. Why is it an *ecosystem*; why not just a regular, old *system*? An ecosystem, by definition, is comprised of interconnected parts, with the behaviors of many individual agents affecting one another as well as the environment's overall holistic pattern. It's a dynamic system, in the engineering sense, involv-

ing many dispersed, interdependent, interacting elements, and, notably, it's not guided by some top-down, centralized control. Some portions may be structured and designed, while others act or interact with their own agency. Consequently, for our learning ecosystem, how we understand instructional structure and learning is an essential consideration.

THE EXPANDING CONTEXT OF FUTURE LEARNING

To advance instructional theory, it's necessary to expand its design towards a modern, longitudinal view of learning, one that facilitates connectivist principles and seeks to amplify outcomes throughout an array of teaching and learning situations, across multiple contexts, diverse learning objectives, and disparate learning modalities. This section outlines eight principles likely to shape the purpose and application of instructional strategies in this complex future context.

1. Connect diverse learning experiences

Explicit in the "ecosystem" concept are the notions of *diversity* and *interconnectivity*. Most relevant, here, are the diversity of learning experiences and their complex interconnectivity with one other. As humans, all of our experiences naturally affect one another. The question is not simply "how to ensure learning episodes are somehow additive," but rather how to intentionally build meaningful and effective connections among learning episodes that advance overall learning goals. Even within a relatively constrained setting, like a single course, instructors and instructional designers need to broadly consider

multiple and varied learning modes and, importantly, how to help connect learners' experiences across them. As a simple example, consider a semester-long class that incorporates face-to-face seminars, online courseware, an additional smartphone app used to remediate some students, and informal resources, such as videos or blogs, that students find online. Courses that blended these sorts of resources are already common. Part of the challenge, however, is gracefully navigating the available set of learning-resource options and *intentionally* integrating them so that they not only coexist but also correlate.

This mosaic of learning components, of course, is often more complex than this example describes. In reality, learning experiences span multiple formal and informal events, timespans, and contexts, contributing to an ever-evolving trajectory of reconfigured and connected experiences, through the lifespan, across multiple contexts, and intersecting with varying developmental dimensions (such as psychomotor, social, emotional, and cognitive learning). An ongoing challenge for learning professionals, then, will be to help learners integrate these myriad experiences in thoughtful ways.

"

The transitions for learners from K–12 to postsecondary education are significant, and if we really want to learn about accumulated learning, we have to have data systems that talk to each other. In the science standards, we're thinking about the progression of learning over time. Learners need time to digest what they're learning in a deep way.

Heidi Schweingruber, Ph.D.

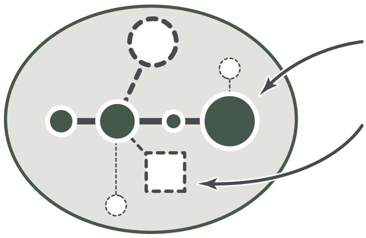
Director, Board on Science Education, National Research Council, U.S. National Academies of Sciences, Engineering, and Medicine

2. Connect to, and enable outside connections from, learning opportunities beyond the planned instruction

The preceding example described the integration of learning resources around a central unifying core (a single course). This is good, but we need to think even broader. In addition to the planned activities designed in or around a particular formal learning event, learning professionals need to consider the impact of learning activities that take place outside of their direct control or even full awareness, such as independent self-directed learning, informal experiences, and other external formal activities (such as courses taught by other teachers on different subjects). Too often, teachers and trainers focus solely on the activities taking place within their purview, that is, within their formal learning episode. This may cause those learning professionals to inadvertently overlook individuals' prior experiences, concurrent learning activities, or the future learning events they might encounter. Linking to prior or external learning isn't new guidance, but the growing availability of well-designed informal learning resources combined with interconnected technologies and interoperable data make these linkages more achievable and more necessary. For the future, it's important to consider instructional strategies that tie-in to these other learning activities *and* also to create "hooks" in the formal learning materials we create, so that learners or other learning professionals can better link our work into their own learning environments.

3. Connect learning across levels of abstraction

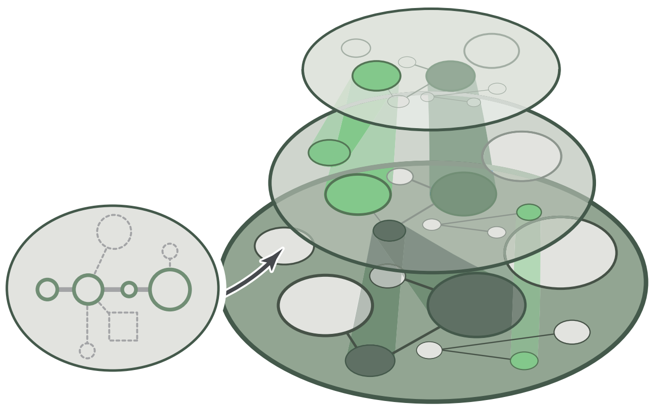
When a child learns to read, we first start by teaching sounds and letters; once these are learned, we teach words, sentences, punctuation, grammar rules, comprehension, and eventually one day maybe professional investigative journalism or creative screenwriting. The point is that different capabilities emerge from the integration of competencies at a given level of analysis. The



"levels of analysis" concept describes the level of abstraction at which something is affected or evaluated, with the implication that the elements at each level relate to one another. Computational neuroscience David Marr has gone so far as to say:

> Almost never can a complex system of any kind be understood as a simple extrapolation from the properties of its elementary components…If one hopes to achieve a full understanding of a system…then one must be prepared to contemplate different levels of description that are linked, at least in principle, into a cohesive whole, even if linking the levels in complete detail is impractical.[7]

In the learning domain, considering learning at different abstraction levels helps us plan the immediate activities (micro-level interventions), broader but still bounded experiences (macro-level interventions), and expansive lifelong learning arcs (meta-level interventions). As indicated in the earlier "Strategies and Tactics; Instruction and Learning" section, precisely distinguishing where one level ends and another begins is less important than the general concept. That concept is that we need to consider is how to better combine the micro- and macro-level approaches to designing instruction (the typical instructional tactics and strategies experienced designers already use) along with new macro-level strategies to create a multidimensional, multilayered model that helps learners aggregate and make sense of learning experiences across devices, modalities, episodes, and learning dimensions. The idea is to support learners beyond the context of a given course or training event, to help them integrate these into a more holistic course of study. For instance, a university mentor might help a graduate student understand how the differ-



ent courses, job-study projects, and internships coalesce—creating integrated meaning beyond their individual parts. How do we provide similar support, but more broadly and outside of a narrow academic context? How do we help people extrapolate meaning across otherwise unconnected activities and integrate experiences in ways that expand those activities' individual values? And how do we do this across longitudinal periods—not only during a semester or academic program, but at a lifelong learning scale?

4. Consider the "in between" learning spaces

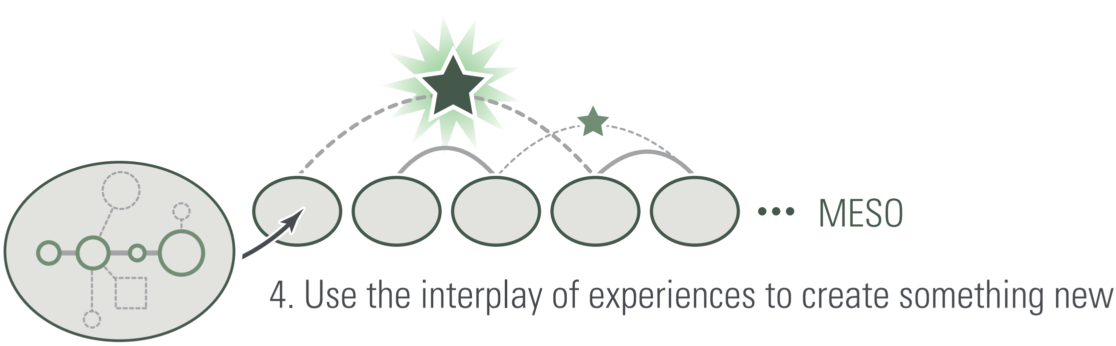
This multilayered model of learning might appear to simply connect pinpoints of learning across time, space, and modality—like a pointillist painting that reveals an image from separate daubs of paint. But the concept goes beyond that. Unlike paint blotches, which are individually contained and otherwise inert, each learning experience is dynamic and complex. Further, the "space" between learning experiences—that is, the new value derived from merging or reconceptualizing learning "frames" in response to their integration or comparison—differs from the largely additive emergent qualities of a Georges Seurat masterpiece. In other words, the challenge for learning professionals is this: How do we capitalize on the abundance and diversity of learning experiences in creative and deeply meaningful ways? Can we do more, for instance, than simply reminding students of prior knowledge or asking working

professionals to consider how new concepts fit into their jobs? Can we build something more than the sum of the learning parts?

Some "levels of analysis" hierarchies include a middle or *meso* level to refer to the connections between the other levels. We're modifying this concept slightly and using the term *meso-level* to refer specifically to those interventions aimed not merely at linking across experiences but also producing unique added value from the correlations. This involves more than just linking across time horizons or subject matters, although those are both relevant. It also involves aggregating concepts at a given level so that new and integrated capabilities emerge.

5. Help learners filter overload

As discussed in Chapter 4, cognitive overload poses a serious problem for individuals, who can readily become overwhelmed by the sheer amount and velocity of information. Learners need new supports that help them filter out "noise" and meaningfully integrate the relevant "signals." If not addressed, we run the risk of increasing information acquisition to the detriment of deep comprehension and robust knowledge construction. The multilayer, interconnected model we've discussed in this section emphasizes this complexity. The challenge for learning professionals is to help learners navigate through information overload and to develop the internal cognitive, social, and emotional capabilities needed to self-regulate against it. Some strategies to support this have been discussed in prior chapters, including social and emotional



competencies (Chapter 4), self-regulated learning skills (Chapter 15), and social learning supports (Chapter 14). Mentoring learners in these areas can help, as can specifically teaching techniques for managing overload including connectivist skills, curation, and metacognition.

6. Help learners use connectivist learning strategies

Connectivism emphasizes the importance of distributed knowledge and capability. For example, rather than knowing how to bake banana bread, one simply needs to know where to find recipes online, how to select the best video tutorials, and which friend to phone when a little extra assistance is needed. Navigating through these technical and social networks is a primary skill—a critical learning strategy—associated with connectivism. Although the multilayered, interconnected model discussed so far has emphasized *instructional* strategies (i.e., those things learning professionals do to help support learning), it's also important to consider *learning* strategies. By definition, these must come from the learners, themselves; however, learning professionals can enhance and support learners' abilities. Instructors and good instructional design can help learners develop their connectivist learning skills and associated self-regulation strategies to help them navigate complex social, cultural, and informational networks.

7. Help learners curate resources and knowledge

Information and communication technologies offer new ways of discovering, organizing, and later retrieving information. Often learning instances and other information can be digitally captured, processed, aggregated, and stored for retrieval across time, contexts, and devices. This notion relates to connectivism, and it highlights the importance of developing related learning strategies (e.g., how to organize and retrieve curated information). Over the last decade, personal learning environments have become popular; these online

systems help learners and their teachers manage learning resources. Looking ahead, learning professionals will need additional tools and mentorship strategies to continue to support such curation activities across increasingly "noisy" and diverse settings.

8. Blend instructor- and learner-controlled strategies

This section has outlined guidance for instructional strategies as well as possible interventions to help develop and activate learners' own internal learning strategies. This final item highlights that both internal expert-directed learning controls as well as learner-directed self-regulatory interventions are critical. Over time, individuals should develop the desire and ability to exert more independent control. However, many learners need help cultivating their self-directed learning abilities, hence a negotiated mix of instructor-controlled and learning-controlled approaches is needed. The role of the instructor in these new multidimensional contexts, therefore, needs to expand and grow in flexibility, shifting to encompass the roles of activator, facilitator, coach, mentor, and advisor.[8]

STRATEGIES FOR MEANINGFUL FUTURE LEARNING

The prior section outlined eight principles for the application of instructional strategies in the future learning ecosystem context; however, it didn't describe the strategies, themselves. Hundreds of instructional strategies and, likely, thousands of corresponding tactics have been tried and tested. Rather than provide a litany of these, we've identified five generalizable principles of meaningful learning well-suited for instructional strategies in this context.

These methods will help create **active**, **constructive**, **cooperative**, **authentic**, and **intentional** learning interventions.

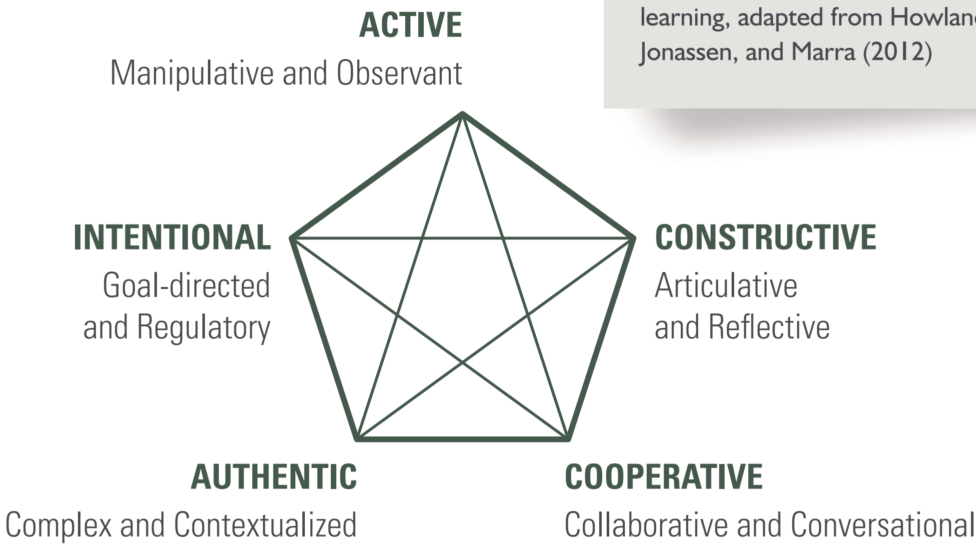
Meaningful learning is grounded in and driven by epistemological orientations and theoretical foundations that are primarily constructivist, social constructivist, and connectivist in nature. In constructivism, learning is characterized as "constructing" or creating meaning from experience such that knowledge comes from our interpretations of our experiences in an environment and emerges in contexts where it's relevant.[9] In other words, the mind filters inputs from an environment or experience to produce its own unique reality or understanding. Therein lies the intentional (goal-directed, regulatory), active (manipulative, observant), constructive (articulative, reflective), and authentic (complex, contextualized) principles of meaningful learning. In social constructivism and connectivism, learning becomes a process of collection, reflection, connection, and publication.[10] Therein lies the cooperative (collaborative, conversational) principles of meaningful learning.

Strategies in Application: An EMT Example

Consider an example of a young woman who, upon high school graduation, enrolls in an Emergency Medical Technician (EMT) training program. The program incorporates multiple courses delivered via didactic instruction and labs, followed by integrative in-the-field clinical experiences. Throughout the program, her learning is supplemented by various digital tools including e-books, practice simulations, and a micro-learning study app.

At a micro-level, the instructional strategy of **scaffolding** can be used to create a supportive and responsive environment to help the novice EMT progress towards becoming a paramedic. Scaffolding involves assessing what learners can do, helping them reflect on what they know, identifying needs and goals, providing individualized assistance towards these goals, and offering opportunities for learners to internalize and generalize their learning. In this ex-

The characteristics of meaningful learning, adapted from Howland, Jonassen, and Marra (2012)



ample, the instructors might engage the EMT trainee in intentional, goal-directed, and regulatory behaviors to prompt a connection between what she learned in the EMT training course and how she can extend the physical and cognitive dimensions of EMT training into future paramedic training.

The instructional strategies of **modeling and explaining** can also be used to help transition learners in their learning trajectories. In modeling and explaining, instructors demonstrate a process while also sharing insights beyond the obvious, such as telling learners about why a task is performed in a certain way. In the case of the EMT trainee, her instructors—whether human or AI coaches—can model and explain what, how, and why paramedics perform certain procedures while also demonstrating the social and emotional aspects involved in these tasks. Modeling and explaining can take place in authentic contexts, which helps present the concepts at the appropriate level of complexity and portray the interplay of dimensions associated with them. For instance, for the EMT example, this could be done in a simulated or real ambulatory run. The EMT trainee, in this case, might be asked to articulate,

reflect, and engage in constructive thinking through observation of expert performance. She might also be challenged to extend her knowledge beyond her comfort zone, such as to consider the next phase of her professional and personal development as a future paramedic.

In addressing more macro-level instructional interventions, we can expand traditional strategies to incorporate organizational, elaborative, exploratory, metacognitive, collaborative, and problem-solving elements across the various dimensions of learning. These macro-level strategies can be connected or "threaded" to incorporate higher-level objectives, such as encompassing a defined career path or advancing a current professional situation. Each individual's journey through a lifetime of formal and informal experiences is somewhat unique and may incorporate multiple contexts and educational events. Hence mapping and organizing a learner's cohesive transition, with the important consideration of "the spaces in-between" (the meso-level of design), as well as the integration of instructional experiences and major life events, become important areas of focus for future learning design.

Upon completion of paramedic training, **coaching and mentoring** can be used as crossover instructional strategies to further scaffold learners towards the next phase or experience in their lifelong learning trajectory. Coaching and mentoring are related. They involve observing learner performance and offering assistance to bring it closer to expert performance (coaching), as well as acting as role model, advising, and supporting learners in attaining goals and in overcoming barriers and challenges (mentoring). As learners set goals for real-life situations, coaches and mentors provide support through dialogue, with social negotiation, and by engaging learners in actively seeking information, researching the issues, and finding solutions to meaningful and authentic problems.[11]

In the EMT example, this means engaging the EMT trainee, who (let's say) is now a paramedic, in **authentic** (complex, contextualized) and **cooperative** (collaborative, conversational) activities to help her think about how to extend

STRATEGIES FOR MEANINGFUL LEARNING

Instructional strategies such as scaffolding, modeling and explaining, and coaching and mentoring can support meaningful learning within and across different levels: [12]

COOPERATIVE (collaborative, conversational)

- Enable collaborative and conversational interactions between learners and instructors, mentors, tutors, or instructional systems
- Encourage learners to engage in collaborative and conversational activities through sharing ideas, listening to each other's perspectives, and co-constructing knowledge
- Help learners work together in communities to accomplish the task at hand

AUTHENTIC (complex, contextualized)

- Use authentic processes and contextualized examples to present concepts and domain knowledge at appropriate levels of complexity
- Engage learners in authentic activities that are complex and contextualized
- Encourage learners to actively seek information, research issues, and find solutions to meaningful and authentic problems

CONSTRUCTIVE (articulative, reflective)

- Enable active and constructive learning by challenging learners to perform beyond their comfort zones
- Engage learners in active and constructive thinking, for instance, by representing their understanding in different ways, using different thought processes, and challenging them to develop and defend their own mental models
- Create opportunities for learners to think constructively while considering experts' performance, articulation, and reflective practice

INTENTIONAL (goal-directed, regulatory)

- Encourage goal-directed and regulatory behavior by keeping learners' intentions at the forefront of the learning task
- Engage learners in reflective and intentional behavior, encouraging them to analyze their actions, compare them to others, and, ultimately, to form expert knowledge and skills
- Help learners set achievable goals and manage the pursuit of these goals through a process of exploration and inquiry

ACTIVE (manipulative, observant)

- Engage learners in active learning through observing the consequences and results of their actions and by assessing and evaluating their knowledge
- Enable learners to consciously think about their observations and actions thereby constructing new knowledge and restructuring their understandings accordingly

her physical, cognitive, emotional, and social knowledge of being a paramedic further, maybe encouraging her to consider the perspectives of a physician's assistant. This might involve shadowing a physician's assistant at a hospital, observing what they do, and actively considering how her current and emerging medical knowledge and skills as well as her social and emotional competencies (such as bedside manner) might apply. This type of experience allows learners to work in authentic settings, and it engages them in collaborative and conversational interactions with their coach or mentor as well as with their peers. All this enables them to share ideas, listen to each other's perspectives, and co-construct knowledge. As illustrated in this example, the instructional strategies of scaffolding, modeling and explaining, and coaching and mentoring can be used as crossover instructional strategies to create meaningful connections that help learners transition across experiences, set lifelong learning goals, and achieve those goals across the lifespan.

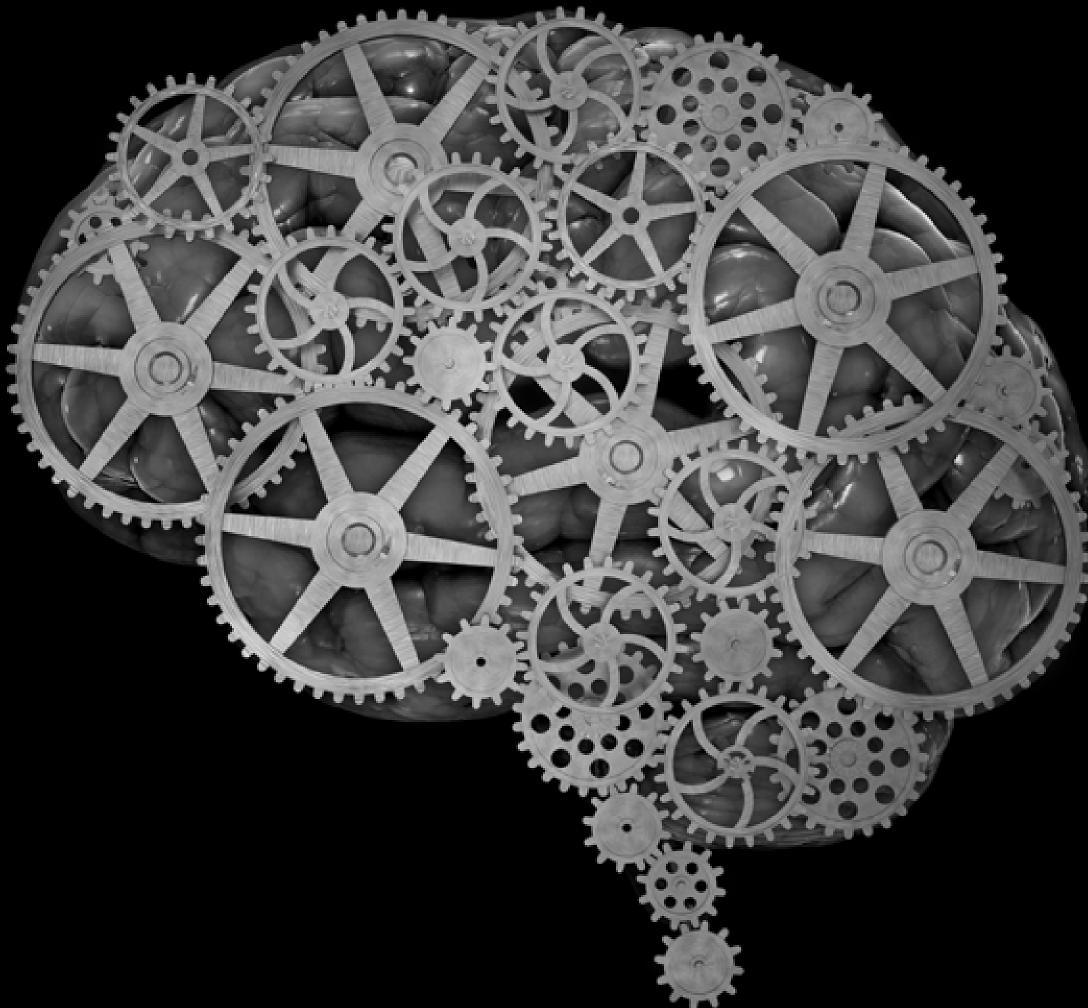
Macro-level instructional strategies can inform larger and larger units of instructional and professional development, and adding meta-level structures also helps support a lifetime of growth across multiple careers, experiences, and interests. This supports continual expansion of knowledge, multiple learning itineraries based on learners' competencies and interests, and multiple tools for manipulating resources. This includes not only formal learning experiences but also informal and life experiences, all intimately connected.

Viewing learning across the lifespan as a networked and connected ecosystem of experiences opens new opportunities for instructional strategies. Each individual may have a different learning trajectory and mosaic of experiences threaded together across education and training, major career events, multiple careers, and other lifetime activities. Like a puzzle that's never quite finished, learners progressively add to their learning landscapes while also benefiting from the integration of the elements within them. The technological advances described throughout this volume have created the capacity to provide learners with connected and cohesive learning across their lifespans.

SUMMARY

Instructional strategies can incorporate interventions, such as scaffolding, modeling and explaining, and coaching and mentoring, to provide the glue that meaningfully supports connected and cohesive experiences across a learner's lifetime. Thinking about the continuum of future learning, we need to consider these strategies at multiple levels—not only within a particular instructional event or course of study, but across learners' longitudinal trajectories. Accordingly, a significant challenge for the future is the differentiated application of instructional interventions across conceptual areas, learners' developmental phases, content modalities, and levels of abstraction—while also considering the impact of composite learning experiences.

Such learning experiences can be implemented using experiential, collaborative, and personalized instructional models that target cognitive, psychomotor, emotional, and social skills across distributed contexts including individual and collaborative activities; these, of course, will also be facilitated by a variety of delivery formats, modalities, and technologies. Thus, we must consider a new model for how to organize and recommend instructional strategies within this non-linear, lifelong, personalized learning continuum. How do we ensure such strategies are coherent to learners and that they improve upon (rather than add noise to) the potentially overloaded learning environment? How do we help teachers, trainers, mentors, and automated systems, as well as learners themselves, use appropriate strategies in this crowded future learning environment? Many other learning science questions persist. However, it's clear that to realize the full promise of the future learning ecosystem, we need to apply considered strategies across it—strategies that combine micro- and macro-level instructional activities with macro-level considerations, that identify and support "the spaces in-between" learning episodes at the meso-level, and that help learners develop and apply their own learning strategies to navigate the complexity of the world around us.



> We need a better system to federate and integrate multiple learning experiences throughout a career, across organizational units. Transcripts have been used for years, for child to young-adult education…but there isn't a good portable transcript system for professionals to securely identify what learning experiences they've completed and their interests to learn related content areas through personalization. As workers move through their organizations and careers, the learning record really should follow them more closely and accurately.

John Landwehr

Vice President and Public Sector Chief Technical Officer, Adobe

CHAPTER 13

COMPETENCY-BASED LEARNING

Matthew Stafford, Ph.D.

Competency-based learning isn't new. It evolved from the following four innovations: The parsing of learning into specific chunks of skills and knowledge; the creation of learning outcomes to clearly establish levels of mastery; assessments that allow learners to demonstrate their mastery; and most recently, a focus on the learner and the learning (*outputs*) versus a focus on the teacher, the curriculum, and the time invested (*inputs*).

The first of these advances traces back centuries to the age of guilds and apprenticeships. Master craftsmen parsed their specialties into a variety of discrete tasks and then trained their apprentices to perform those activities to appropriate levels of mastery. Another remnant of the age of guilds is the concept of varying levels of mastery. Aspiring craftsmen started as apprentices and advanced through the assorted levels. Only after demonstrating mastery of every aspect of the craft, would the tradesman graduate the apprenticeship at the full craftsman status.

This parsed-learning approach still exists across widespread training programs today. The military employs this approach with its enlisted personnel, training and certifying members on specific tasks. One can also see it in industry and, not surprisingly, in the wide variety of vocational-education programs that prepare students for jobs in industry. These modern settings also borrow the performance levels from classic trades-training to indicate progress from novice to master. Ironically, the Air Force—the youngest of the U.S.

Historically, a cooper ("barrel-maker") would train an apprentice on selecting trees and forming the individual staves. Equipped with these skills, the apprentice would progress to assembling the staves into the barrel form, installing the retaining hoops (forged by a fellow craftsman, a blacksmith) and "rounding" the barrel's interior. Next, the apprentice would master the art of finishing the barrel, so it would seal. Then there was the complex task of cutting the *croze*—the groove into which the head and foot rest, installing the head… It was a complex series of tasks requiring a variety of specialized tools! Even after mastering barrel-making, however, an apprentice had more to learn. In addition to barrels, coopers also made casts, vats, buckets, tubs…a sundry of wooden vessels made from individual wooden staves. Only after mastering all of the knowledge, tools, processes, and specific tasks associated with all of the vessels, would the master craftsman honor an apprentice with the title "cooper."

…the unlikely forerunner to competency-based learning

military branches—even employs old "guild language" to label its Airmen's skill levels: 1 for helper, 3 for apprentice, 5 for journeyman, and 7 for craftsman.[1]

Although born in training, the application of this "levels of mastery" approach eventually found its way into education, largely due to research into learning theory. In 1956, for instance, Benjamin Bloom posited specific levels of mastery within the cognitive domain of learning.[2] Equipped with these descriptions, teachers and instructional designers had consistent levels of capability they could target. Well-defined cognitive outcomes mark the second of the four innovations that led to competency-based learning. What educators needed next were authentic assessments to validate that learners had reached the desired levels of mastery. Authentic assessments are

those in which students have to demonstrate *meaningful* applications of their knowledge and skills. A classroom assessment that matches real-world workplace activities, for instance, would be "authentic."

Authentically assessing performance in the cognitive domain, however, is difficult. The mastery of these less tangible concepts—the ability to formulate an effective argument, for instance—is complicated. Demonstrating conceptual mastery is even more so. Educators are forced to "sample" desired behaviors and then, equipped with these samples, make informed judgments on the levels of mastery students have achieved. Over time, educators have progressed in this art, creating performance-based assessments that actually measure levels of mastery, even in "soft skills." Effective, authentic assessments were the third innovation contributing to competency-based learning; however, assessments play a far more important role than simply measuring mastery—they actually drive learning.

Contemporary learning theory, based on evidence-informed research and neuroscience principles, makes it clear that the best results occur when individuals take responsibility for their learning. Terry Doyle, an accomplished learning science author and professor emeritus, is fond of reminding his readers, "The one who does the work does the learning."[3] Assessments can empower learning by making learners *do the work*. For instance, instead of devising detailed courses of study, teachers can instead focus on designing effective assessments, describing them to students, and then helping learners find their own paths to success.

It may sound shocking to some; however, this is how most informal learning occurs. Someone buys a lawnmower and turns to YouTube to figure out its assembly and how to get it running. Someone else goes online to figure out how to change the oil filter in an antique automobile. Gamers have special websites to share tips on how to win in their favorite video games. Even those who sit and practice the lost art of "reading the manual" are benefiting from informal, self-directed learning. In each case, there are no formal classes.

The classical model of education posited learning as a somewhat passive pursuit. Learners sat and listened to lectures or read from books in order to memorize facts.

Learners can spend as much or as little time, as necessary, to achieve their learning goals. The focus is on reaching the desired level of mastery. This learner-centric approach, where the source of learning is less important than the mastery of it, catalyzed the final innovation contributing to competency-based learning.

This innovation is, arguably, the most revolutionary for contemporary learning professionals: In competency-based learning, performance becomes the constant and time becomes a variable. This is in direct contrast to the traditional approach to training and education, where time is constant. In this classical model, learners attend classes that run so many days, in programs that span so many months… The Carnegie credit-hour system, underpinning many U.S. educational programs, exemplifies this time-based approach. Similarly, traditional learning professionals talk of "seat time" or "contact hours." In all cases, time is the constant and performance varies. Some learners sit through an entire course of instruction and master all of the objectives, earning an 'A.' Others, sitting alongside these top performers the entire time, don't do as well. Performance varies.

In competency-based learning, however, all of the learners work to achieve the desired level of mastery. Some will do it the first day. Others will take longer. Further, in these outcomes-focused settings, some learners may show proficiency even before exposure to the prescribed curriculum. Perhaps they already mastered the skills and knowledge in previous experiences. Regardless of the source, if they demonstrate mastery, they earn the credential and

advance in their learning. Others will require a complete program of instruction. Again, *performance* is the constant and *time* is the variable.

Another aspect of competency-based learning that causes confusion is the concept of competencies. There are many different interpretations of this term. For some, it refers specifically to a performance and encompasses knowledge, skills, abilities, aptitude, and self-concept. Others define competencies far more narrowly, describing them in terms of specific skills or specific areas of knowledge. Looking at the definitions below, it is easy to see why there's confusion over the term.

A few of the competing definitions of a competency include:

- "…a clearly defined and measurable statement of the knowledge, skill, and ability a student has acquired in a designated program," per the Southern Association of Colleges and Schools Commission on Colleges.[4]
- "…a measurable pattern of knowledge, skills, abilities, behaviors, and other characteristics that an individual needs to perform work roles or occupational functions successfully. Competencies specify the

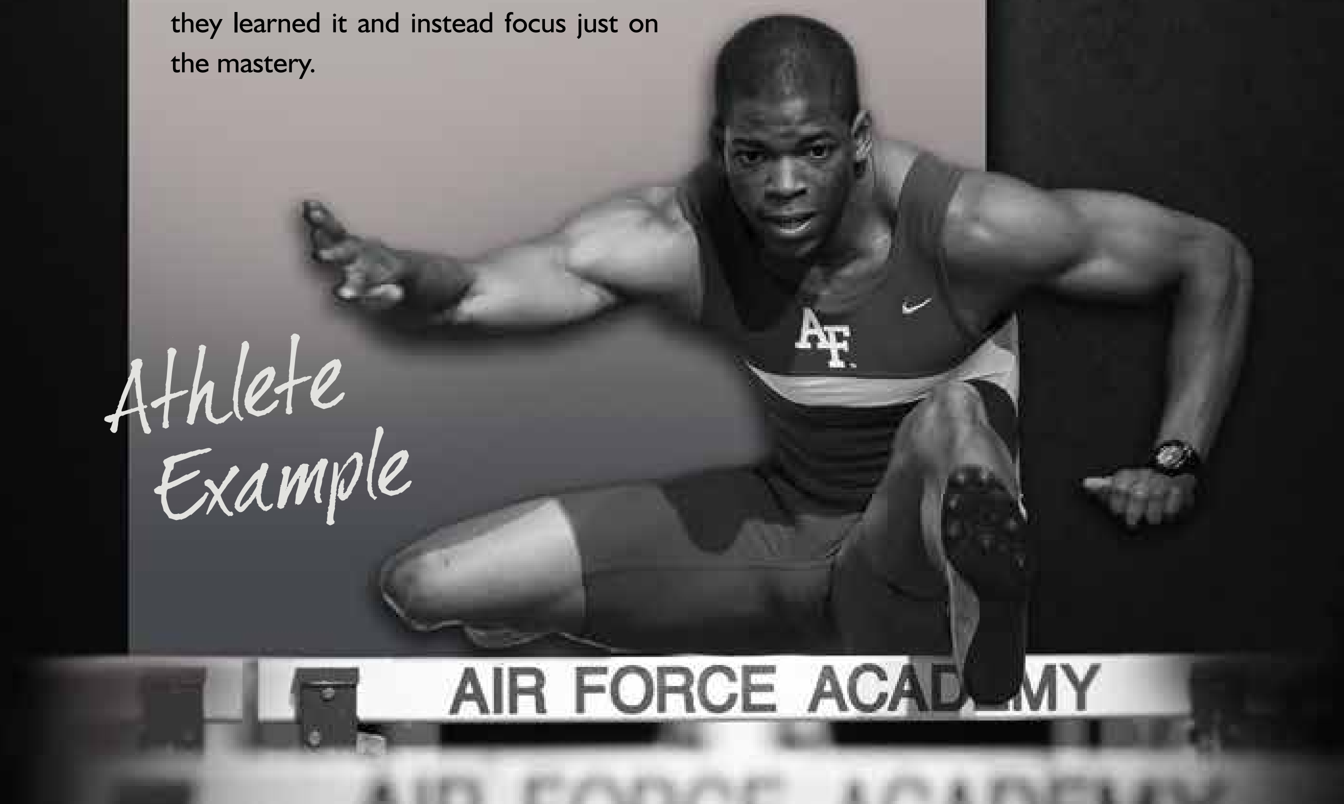
In competency-based learning, performance is key; performance standards are held constant while time may vary.

Suppose a coach goes into the team assembly room and explains: Next Friday, I'm going to put this 48" stick into the ground vertically, like this. I'll expect each of you to jump over it without touching it. Those who do so will accompany me to the track-and-field competition the next day.

What would happen? The traditional approach would be to build a course that teaches athletes how to jump higher. In this instance, however, the coach has turned the learning task over to the learners: Those athletes who want to attend the competition are going to put a 48" stick into the ground and start practicing ways of jumping over it. Some will try a standing broad-jump approach (a vertical leap from a stationary position); others will try a running jump. Still others might try the famous "Fosbury Flop," the popular high-jumping technique where athletes pass over obstacles and land on their backs. Each athlete will approach the task in their own way, leveraging their individual strengths so they can demonstrate mastery of the assigned task.

Harry S. Truman once noted, "It is amazing what you can accomplish if you do not care who gets the credit." In essence, competency-based learning applies a similar level of humility to learning. It's amazing what learners can master if we cease caring how or where they learned it and instead focus just on the mastery.

Athlete Example



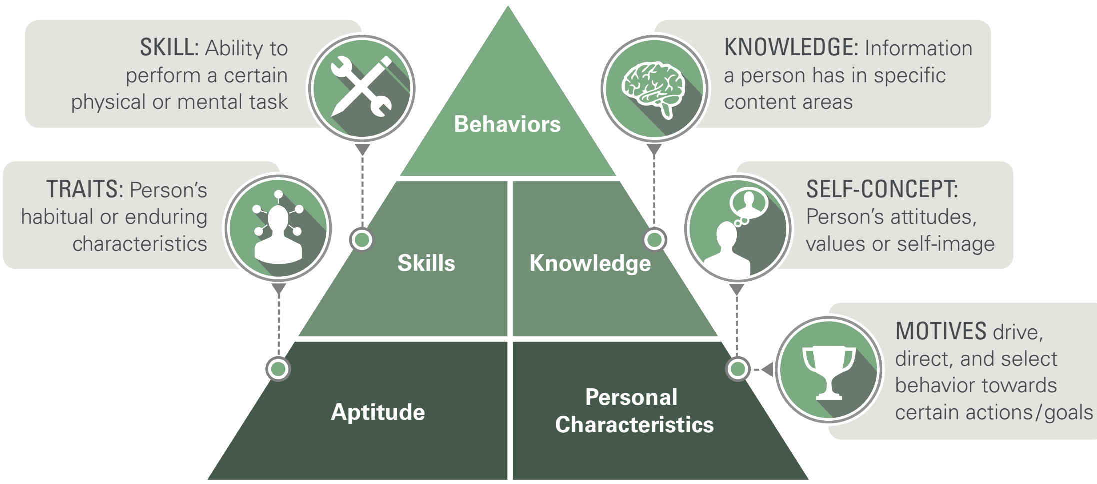
'how' of performing job tasks, or what the person needs to do the job successfully," per the U.S. Office of Personnel Management.[5]

- "…observable, measurable pattern of knowledge, skills, abilities, behaviors, and other characteristics needed to perform institutional or occupational functions successfully," per the U.S. Air Force.[6]
- "…a student's ability to transfer content and skill in and/or across content areas," as defined in the book, *Off the Clock*, which outlines a roadmap to competency-based education.[7]

Some commonalities exist among these definitions. Like most competency definitions, these focus on capabilities that are transferable across a range of performance requirements, inherent in which are the notions of functional utility and portability. These definitions also highlight knowledge and skills; the more holistic definitions, however, look beyond these two facets to also include other capabilities that may impact competence. In their 1993 touchstone work on competencies, *Competence at Work*, Lyle and Signe Spencer listed five components of competencies: [8]

- **Motives** – Motives drive, direct, and select behavior towards certain actions or goals and away from others
- **Traits** – A person's habitual or enduring characteristics
- **Self-Concept** – A person's attitudes, values, or self-image
- **Knowledge** – Information a person has in specific content areas
- **Skill** – The ability to perform a certain physical or mental task

In their 1999 work, *The Art and Science of Competency Models*, Anntoinette Lucia and Richard Lepsinger offered a slightly different conceptualization.[9] Readers can see in the above figure how Lucia and Lepsinger's approach correlates with Spencer and Spencer's; however, the pyramid provides better insight into the ways in which some characteristics support others and how, when combined, they all manifest in behaviors—i.e., in performance.



The Competency Pyramid per Lucia & Lepsinger, with definitions from Spencer & Spencer

Lucia and Lepsinger argued that aptitude and personal characteristics are foundational, and while such characteristics may be innate, they can be influenced. Skills and knowledge, of course, are more easily affected; they can be imparted through training and education—through *development*. At the top of the pyramid, all of the characteristics manifest in behaviors—in *performance*.

There are two categories of competencies within most institutional models, *core* and *occupational*. Core, or "institutional," competencies are applicable to everyone in the organization. Occupational, or "specialty," competencies are applicable only to certain vocational specialties, positions, or jobs. For instance, every employee of a city would need at least some level of proficiency in "teamwork and cooperation" or "initiative," but only firefighters would need to master a firefighting competency.

The applicability of competencies to skills development (like firefighting) is, for most, more easily understood than the relationship between competencies and *cognitive* development. This partially explains why competency-based learning has been adopted more slowly in education than in training. Within

the scholarly literature, however, there are many examples of purely cognitive competencies, such as analytical thinking, critical thinking, conceptual thinking, diagnostic skill, and commitment to learning, to name a few. Like their vocational counterparts, these cognitive competencies are transferable—applicable to a wide variety of educational pursuits.

Using Competencies to Guide Learning

Competencies serve as broad targets for learning. Readily available to both learners and teachers, they serve as a "contract" for learning and describe the "finish line" for the accompanying learning experience. When learners achieve desired levels of mastery in all assigned competencies, they progress to subsequent learning events or complete their programs.

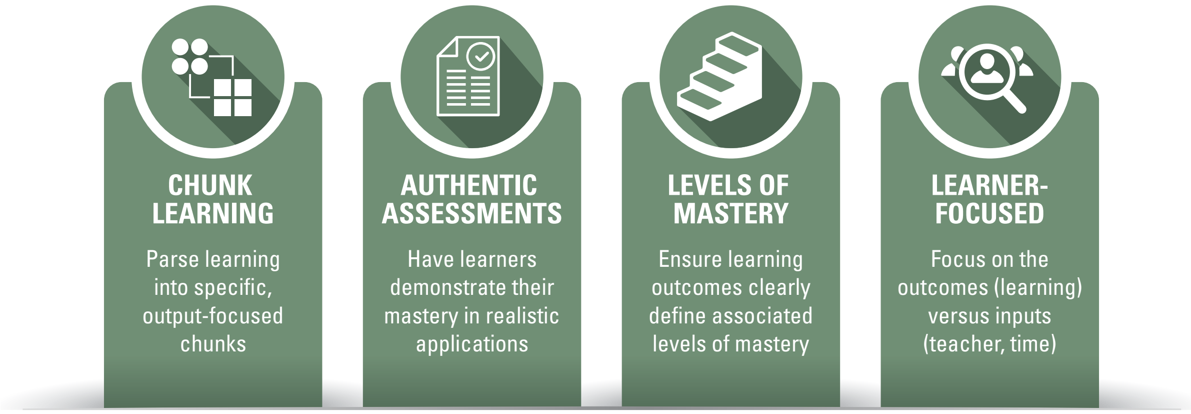
A well-crafted competency model will typically list competencies, provide definitions, and be accompanied by descriptions of proficiency-levels. As positions are created, as workers are hired, or as students move through educational programs, competencies and desired proficiency levels are selected. Supervisors, trainers, and faculty members then devise learning experiences and assessments to ensure their people can reach and demonstrate the desired levels of learning. Once the desired competency is demonstrated to the required level of mastery, the performance is *credentialed*—captured in a certificate, badge, or other record, so there's a lasting record of this capability.

Tracking competency development facilitates learning portability. For instance, by credentialing competency completions, learners can prove they possess given capabilities, which is useful for meeting the entry criteria of future learning experiences or for verifying personal qualification should they move to other jobs. Similarly, tracking competencies gives parent organizations more opportunity to effectively employ workers' skills and knowledge, that is, organizations can move workers to those areas where their competence is most needed.

Because competency-based learning facilitates precision in tracking and employing developmental investments, it's popular within industry. It's particularly valuable to employers hiring new workers. Prior to competency-based learning, employers had to assume that prospective employees possessed the required attributes, attitudes, skills, and knowledge simply based on their formal learning credentials and the limited time spent in interviews. It's an unreliable approach. Just because prospective employees have high school diplomas, for instance, offers no guarantee they can perform the arithmetic needed to make change at a cash register or even to read its operating instructions! In contrast, since competencies aren't awarded until mastery performance has been demonstrated, employers see exactly what their prospective employees know and can do. They've demonstrated and received credentials for these capabilities prior to applying for the job.

Competency-based learning is not yet universally accepted within education, but acceptance is growing. One of the more interesting experiments, in this vein, is described in Fred Bramante and Rose Colby's book, *Off the Clock: Moving Education from Time to Competency*.[10] Bramante served as the Chairman of the New Hampshire Board of Education where he faced a high-school dropout rate of 20%. To address this, he led the school system to embrace competency-based learning, implementing his approach in 2009. By 2011, the cumulative dropout rate was 4.68% and still falling. Students were mastering the competencies necessary to earn their high school diplomas but doing so in nontraditional ways. The key was focusing on the learners and the learning—the outcomes. This is at the heart of competency-based learning.

Post-secondary institutions are also gradually embracing competency-based learning. Educators have found students enjoy the flexibility and the fact that they can progress as quickly through the programs as their efforts and capabilities allow. Western Governors University was an early adopter of competency-based learning; however, the benefits of the approach quickly attracted others. The University of Michigan, the University of Wisconsin system, Pur-



Considerations for Competency-Based Learning

due University, Northern Arizona University, and Southern New Hampshire University, among many others, are offering competency-based programs.

CONCERNS

Minimizing Learning

Perhaps foremost among the competency-based learning detractor arguments is the concern that in the rush to impart marketable skills for students, the competency-based learning institutions are pushing students into "knowledge-less" versions of the traditional liberal learning. In other words, those seeking to discredit competency-based learning claim it's too utilitarian and specific, at the expense of broad-based learning and critical thinking. While such programs lead to a skilled and potentially employable workforce, critics argue the upward mobility of those workers is limited in terms of perspective and their potential to step outside the initial knowledge specializations. This argument also implies (or sometimes openly alleges) that the true aims of competency-based programs are to expedite program completion and ensure high graduate-to-employment statistics, which help sell these programs to future students. Detractors argue competency-based learning institutions are

K–12 SCIENCE STANDARDS: The development of the Next Generation Science Standards is an innovative example of bringing research-based learning to scale. The National Academy of Science, Engineering, and Medicine developed the Framework for K-12 Science Education informed by research on learning that is developmental and interweaves science and engineering practices with core ideas and crosscutting concepts. Moving from the Framework to standards with clear performance expectations came with a hand-off to Achieve, an education nonprofit established in 1996 by governors and business leaders that works with states to prepare students for college and career readiness.

Achieve reached out to states inviting them to be lead state partners in developing the standards to an overwhelmingly positive response, resulting in 26 state partners. This was the start of the tag line, "For States, By States." The collaborative approach continues to today with the launch of Achieve's Science Peer Review Panel to enhance the implementation and spread of high-quality lessons aligned with the Next Generation Science Standards. Creating a sense of ownership and the providing tools to implement. To date, 19 states and the District of Columbia have adopted the Standards, and 21 additional states have developed their own standards based on the Framework.

Susan Singer, Ph.D.

Vice President for Academic Affairs and Provost, Rollins College

www.nextgenscience.org/framework-k-12-science-education

creating a new hierarchy within the educated populace: A distinction between those who receive a "cheap, fast food-style or 'good enough' education from those who receive a quality one."[11] Said another way, the concern is that competency-based learning graduates receive a lower quality of education more pointedly focused on vocational development than on habits of the mind, and that habits of mind (supposedly in contrast to the attained competencies) are more transferable and, ultimately, more valuable beyond entry-level positions. It's a position worth noting.

Quality

Competency-based learning certainly has the potential to be of lower quality. The concern is not so much about competency-based learning, in general, but in how competency-based learning is operationalized within individual institutions. A vocationally focused program that grants credit for demonstrating acceptable levels of supporting, transferable skills, such as speaking, writing, critical thinking, and active listening, might indeed produce graduates who aren't on par with their peers from traditional higher-education institutions, who've had to delve more deeply into these areas as part of their academic experiences. Again, however, *it depends*. It depends on the assessments used within the vocationally focused programs and the degree to which the transferable skills were tapped and reinforced during the program. If an institution sets its requirements for performance very high, it can force all but those who have that level of mastery into its more traditional learning opportunities.

Employing Competencies Effectively

Perhaps the most important concern raised over competency-based learning isn't actually a rejection of the concept but, rather, concern over how it and the resulting competencies are employed. In 2003, George Hollenbeck and Morgan McCall questioned why the competency-based approach to executive

development hadn't produced better executives. They wrote:

> As we begin the 21st century, evidence abounds that executive and leadership development has failed to meet expectations. Unless we change our assumptions and think differently about executives and the development process, we will continue to find too few executives to carry out corporate strategies, and the competence of those executives available will be too often open to question. The "competency model" of the executive, proposing as it does a single set of competencies that account for success, must be supplemented with a development model based on leadership challenges rather than executive traits and competencies. Executive performance must focus on "what gets done" rather than on one way of doing it or on what competencies executives have.[12]

Hollenbeck and McCall weren't calling for the rejection of competency-based learning but were simply arguing that it's not sufficient to develop or possess individual competencies; instead, it's how they're collectively employed that's truly important in terms of occupational success. By way of a metaphor, one can produce the perfect brick (the competency), and with a stack of these bricks, one can build a cathedral that soars into the sky or a brick outhouse. It's how one employs competencies that matters. This is a valid concern. Application is all important.

U.S. AIR FORCE EXAMPLE

The U.S. Air Force is attempting to integrate competency assessment and the credentialing of mastery into its workplace. The Air Force can do this because, unlike most learning institutions, it has a continuing relationship with the graduates of its education and training programs, which affords unique opportunities to ascertain the impact of learning within the work environment. The effort is already attracting interest even though it's yet to be executed. Air Force administrators predict the assessment and tracking mechanisms will be online by 2022. This use-in-the-workplace example segues to the final competency-based learning concern, the attachment to talent management.

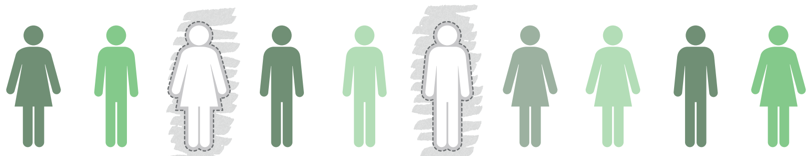
VISION

A national competency-based system will enable a great deal of flexibility.

Learners will learn at their own pace. A common characteristic of competency-based learning is that it enables learners to advance as they reach mastery because the focus in on outcomes (i.e., mastery of the given competencies) and not on the amount of time spent completing a set curriculum. Said another way, if a learner can prove mastery of a "communication – speaking" competency, developed earlier in life, she won't have to sit through a class rehashing the material. More than that, articulating competency models helps clarify the instructional domains and give structure to learner models—both of which aid personalization and automated adaptation of learning. This, in turn, allows learning to be tailored to individuals in multiple ways, not only targeting their individual strengths and weaknesses, but also helping to optimize the availability of instructional opportunities, plan personal schedules, and so on.

Competency-based learning will also increase resource efficiency. Allowing learners to bypass education and training requirements for competencies they've already mastered can accelerate individuals through programs. Perhaps they can use this time to pursue other competencies or, instead, they might need to employ the competencies they've mastered on the job. Either way, learners and host institutions only expend resources on competence evaluation and on aiding those learners working towards mastery.

Competency-based learning can help individuals better tailor their planning and learning priorities. If, for instance, a learner is working while attempting to master a list of specific competencies, he might choose to "front-load" those competencies most vital to short-term success on the job. Learners might also leverage insight into the competency requirements to choose a learning methodology that they find more effective for themselves or to help inform future career planning. Consider this example: The figure on page 260 shows



> So much of our education system is based on where you live and how much money you have. We're lacking national equity. But if you learned it, it should count. I don't care where you learned it. Lots of people aren't being served by the current system, but they should be. By 2025, 60% of Americans will need a postsecondary credential. We currently don't have a system that can produce those results unless we leverage every postsecondary learning opportunity and everyone together.

Amber Garrison Duncan, Ph.D.
Strategy Director, Lumina Foundation

an excerpt from the Department of Energy's 268-page catalog, *Leadership Development Seminars July 2013–2014 Edition*. It links learning opportunities both within and beyond the government to aid employees seeking to master the Executive Core Qualifications (i.e., the competencies specific to executive-level leadership for the Federal Senior Executive Service).[13] The Department of Energy's catalog includes government-offered courses, courses offered by various universities and private industry organizations, and even informal learning opportunities—all mapped to the same set of Executive Core Qualifications. Such correlations provide an invaluable tool for motivated learners to build competence in areas specific to their employers' needs.

Equity and Diversity

A less obvious benefit of competency-based learning is the manner in which it may help address inequities within the U.S. populace. The Lumina Foundation has researched this, noting that competency-based learning offers

a mechanism to get education into the hands—and minds—of disadvantaged Americans.[14] This includes under- or unemployed adults, adults with some college exposure but with no credential, and historically underserved communities. Education has long been credited as a bridge from poverty to prosperity. Competency-based learning expands access to that bridge.

Translation

Competency-based learning is growing as a "currency" for learning. The transition from the Carnegie, credit-hour based approach to transcripting education is underway. The Lumina Foundation, an independent, private foundation in Indianapolis, has set for itself *Goal 2025*, a goal to have 60% of U.S. working-age adults possess meaningful and marketable learning credentials beyond a high school diploma by 2025.[15] To achieve this, the Foundation is pressing for, "A new, national system of transparent quality credentials" and "a national expansion of competency-based learning…that recognizes measuring academic progress based on demonstrations of what students know and can do." A leader in competency-based learning, Lumina is working with learning institutions and governmental organizations across the U.S.—and they're not alone. The U.S. Department of Labor, U.S. Department of Education, U.S. Office of Personnel Management, and elements of the U.S. Department of Defense are also pursuing competencies.

There is talk of a "Rosetta Stone" to translate competencies, so associated credentials can move more easily across organizational lines, expediting individuals' progress towards their learning goals. Given the rate at which new competency models are entering the marketplace, however, this might not be the best approach. Leveraging the "currency" metaphor—which is enormously popular among competency-based learning proponents—is helpful. A "Rosetta Stone" would serve as a sort of "currency calculator" to compute exchange rates among credentials. That would be a complicated process. Part of the challenge, however, is that one may not be able to track the exchange rates

Department of Energy Learning Opportunities Correlated to Executive Core Qualifications

The U.S. Department of Energy's *Leadership Development Seminars July 2013–2014 Edition* links learning opportunities both within and beyond the government to aid employees seeking to master the Executive Core Qualifications. This catalog lists over 550 courses offered by the U.S. Office of Personnel Management as well as 75 universities, colleges, and private industry organizations throughout the continental U.S. and more than 700 leadership readings, mapped to various Executive Core Qualifications. Each listing is cross-referenced and includes a brief description of the course as well as its date, location, cost, and contact information.

Note: The listing of these courses does not constitute endorsement of their content by the U.S. Department of Energy or any agency of the U.S. Federal Government.

for every currency interaction (pesos to dollars, dollars to rubles, and fenings to pesos, for instance), particularly as their values fluctuate. There would be so many different currencies to track! Why not leverage the same approach used for different currencies? Evaluate the relative value of the currency in relation to commodities. If one knows how many of a given currency it takes to purchase a commodity, such as a loaf of bread or barrel of oil, currency conversion is easy.

Within a competency-based system, the commodity is performance—what individuals know and can do. Hence, to exchange competency information among institutions, these organizations needn't learn one another's competency models; they need only focus on what those competencies can "buy," that is, the credentialed performance.

However, credentials are only as effective as the reliability of their measurements, and some challenges still remain in this area. For instance, the same competency may manifest differently in different contexts. For example, seemingly universal competencies, such as leadership, may vary widely between professions. As leaders, surgical doctors need more procedural knowledge than business leaders who, in turn, may need more skill in motivating their staff to increase sales. Therefore, while some competencies have similar "bundles" of required knowledge, skills, and other attributes, others require different components sets to determine applied competency. Credentialing bodies must take these issues into consideration when determining how to assess and manage credentials for competencies.

Another challenge involves determining the evaluation criteria for performance standards; this can be particularly difficult. Some questions to ask are: What methods will be used to assess performance (tests, portfolios, writing)? Who's responsible for the assessment? How will these assessments be used?[16] Clearly, there are numerous questions to address before an integrated, overarching competency-based system can be realized. However, the subsection below outlines some recommended ways forward.

> The currency of the future labor market will be skills or competencies, which will demand competency-based education in both early-life and lifelong learning.
>
> **Martin Kurzweil, J.D.**, Director, Educational Transformation Program, Ithaka S+R

IMPLEMENTATION RECOMMENDATIONS

1. Decide if competency-based learning is right for the organization

The first step in embracing competency-based learning is to conduct a comparative analysis of the change versus the status quo. What's the demand for competency-based learning? Can it enhance learning effectiveness and efficiency within the institution? Are the leaders supportive? Are the faculty and staff supportive? Is there sufficient talent to create the competencies, the resulting competency model, the levels of mastery, and the assessments so vital to competency-based learning's success? Albert Einstein is reported to have said, "If I had an hour to solve a problem, I'd spend 55 minutes thinking about the problem and five minutes thinking about solutions." Before embarking on a change to competency-based learning, consider carefully the potential benefits and challenges. Make sure that the investment will pay sufficient dividends. Lastly, make sure that the organization is willing to make the journey, too. To understand the relative value of the competency-based learning approach, consider other organizations that have already embraced it. Find

organizations similar to your own with similar missions and challenges. Look at what they did to embrace competency-based learning and how they've employed it. …and as much as possible, learn from others' mistakes!

2. Build a competency model

Next, construct and validate a competency model. There are several approaches one can take. Many institutions simply select from existing models where the competencies, performance levels, and other accoutrements seem to fit their needs, modifying their model as needed during validation. A second method is job analysis. With this approach, researchers dissect the various jobs performed within an organization figuring what core and/or occupational competencies are required and at what proficiency levels. Typically, the researchers will interact with workers to ensure the analysis is thorough and that all competencies have been properly identified. Another method involves leveraging panels of experts, surveys, and interviews to create a competency model. This is a fairly common approach and benefits from the fact that most organizations fail to capture the full breadth of tasks and knowledge within the human capital management documentation. A final method, and one rated most effective by experts, is a criterion sampling method. With this approach, researchers work with organizational members to establish criteria to identify the most outstanding performers. Applying this criteria, the researchers then interview these performers to determine "what makes them tick" and what competencies make them so successful in their jobs. The resulting model helps drive workforce development by focusing on the competencies most closely aligned with success—outstanding performance—thus benefiting both the employer and employees.

Validation can occur simultaneously as the model is being created. In essence, *validation* is a means to ensure the predictability of the competency model. If an employee who reaches the prescribed level of mastery in each of the listed competencies is judged to be an outstanding employee, then the model

has a high degree of predictability and validity. If, however, those employees who reach all of the desired levels of mastery are still found wanting, then the model probably needs more work. With predictability—the "gold standard" for competency models—it's easy to see why criterion sampling is a preferred method for creation and validation. Perhaps not surprisingly, starting with top personnel offers a shortcut to creating a model capable of predicting outstanding performers!

3. Develop authentic assessments for competencies

Once a model has been successfully created and validated, the next step is to develop authentic assessments through which learners can demonstrate levels of mastery. For industrial and vocational organizations, assessments can be based on actual job performance. For most technical skills, workers need only demonstrate their ability to perform their work-specific tasks correctly to earn certification for a given level of mastery. For "soft skills" and cognitive competencies, the assessments are usually more difficult. As noted previously, educational programs usually rely on samples of behavior and faculty judgment to assess competency mastery. A student required to demonstrate mastery in multiplication, for instance, with levels of mastery determined by the number of digits in the numbers being multiplied, would never be asked to multiply every possible combination of appropriate-length numbers. That would be ridiculous. Similarly, a student required to construct and deliver persuasive arguments would only have to perform this task a limited number of times before a faculty member felt confident in certifying a level of mastery in the task.

There are standardized tests for soft skills, for example the *California Critical Thinking Skills* test and a number of leadership and communication assessments. The key to building or selecting assessments is to ensure they're *valid* (i.e., assess what they are supposed to assess), *reliable* (i.e., consistently produce similar results), and *authentic* (i.e., match similar challenges learners will encounter outside of the classroom—in the workplace, for instance).

O*NET – OCCUPATIONAL INFORMATION NETWORK

Sponsored by the U.S. Department of Labor, O*NET provides a database of general occupational descriptions, including typical job and employee attributes, necessary skills and knowledge, and workplace characteristics. These are provided as free, open-access resources for broad use across businesses, educators, job seekers, and HR professionals. To date, O*NET contains standardized descriptors for nearly 1000 occupations across the U.S. economy; these form a common foundation for codifying occupational competencies. Looking ahead, O*NET developers are exploring ways to create an overarching architecture across competency frameworks, and they're starting to use GUIDs (Global Unique Identifiers) to connect credentials to O*NET competencies. Ultimately, O*NET developers imagine this work will remake the resumé, perhaps turning it into a clickable or drill-down document that contains someone's entire "competency portfolio" but at levels of detail usable by employers. Further, the capability to relate bundles of competencies to specific education and training modules, classes, or sequences of courses could enable help individuals determine what competencies they need to achieve their career goals, and how to, or where to go, to acquire those capabilities.

4. Develop learning paths to reach desired mastery

This is where creativity and ingenuity can pay big dividends. If program leaders pursued a criterion-sampling approach to creating and validating a competency model, they may be able to ask those outstanding performers, "How did you learn that?" The same is true of others able to demonstrate mastery of competencies without taking any institutional classes or courses. The answers can be fascinating. It may turn out, for instance, that an employee

> There's no such thing as "nontraditional" education anymore.
>
> **Fred Drummond**
> U.S. Deputy Assistant Secretary of Defense for Force Education and Training

who demonstrates mastery of "leadership," gained the associated capabilities through the process of earning a Gold Award (Girl Scouts) or Eagle Scout (Boy Scout) designation as a child.

Of course, many students and workers will need help in mastering core and occupational competencies. It's tempting to offer a single course that covers a wide variety of topics, competencies, and proficiency levels; however, focused learning, addressing the specific desired competencies and proficiency levels, coupled with sufficient time for reflection and practice, is key. Further, it's more efficient: Institutions invest only what's needed to achieve success, and learners don't waste time or effort picking up unnecessary or duplicative skills and knowledge. Obviously, this applies more specifically to workplace-learning than to educational applications. Development of the cognitive competencies so foundational to education requires a depth and breadth of learning far broader than a specific vocational focus.

As noted earlier in the "athlete example," one needn't create a program or course for every learning need. Immersive learning experiences, such as special work assignments, often allow learners to reach their goals more effectively and efficiently than formal classes. Another option to consider is the guild approach, as addressed at the start of the chapter. Maybe assigning an "apprentice" to a "craftsman-mentor" is the key. Also, one shouldn't exclude off-duty, nontraditional learning. For instance, an employee or student struggling with public speaking may not need a speech class; perhaps joining a local Toastmasters club will foster her skills. Hence, it's useful to document the various ways other people have developed their own capabilities; these can serve as models and potential pathways for those seeking to earn their own credentials. Consider accumulating this information into a catalog,

where learning experiences are cross-referenced to specific competencies and proficiency levels.

5. Lastly, organizational leaders need to ensure there's a mechanism for tracking and reporting competency mastery

This isn't a simple task. Those responsible for this will have to consider the broad array of users who need access to the information. Certainly, learners need to know how they're progressing—where they're strong, where they're weak, and what they need to do to achieve their learning goals. For educational institutions, faculty and staff will need access to the information. There's also a need for transcripting learning progress for sharing with learners and other institutions. Industrial entities will have a variety of data-users as well. Like students, workers will want to know where they stand. Supervisors will

TECH TOOLS EXAMPLE: JDX

The Job Data Exchange (JDX) is a new set of open data resources, algorithms, and reference applications for employers and their HR technology partners to use in improving how employers communicate competency and credentialing requirements for in-demand jobs. Today, 50% of open, available positions in the U.S. country go unfilled because employers can't find the right talent for their critical positions. At the same time, education, training, and credentialing providers are in need of better, faster, clearer signaling from employers on what skills are most in demand in a changing economy. The JDX isn't a "job board," rather, it will be a resource for employers and their HR technology partners to more clearly define competency and credential requirements for jobs distributed to talent sourcing partners such as job boards and preferred education, training, and credentialing partners. The U.S. Chamber of Commerce Foundation and their parters are pilot testing the JDX throughout 2019 across six states and the District of Columbia.

See: www.uschamberfoundation.org/workforce-development/JDX

want to know how their individual workers are progressing in their development, and also where their teams are strong or weak in terms of needed competencies. Similarly, progressive levels of supervision will want insight into this aspect of workforce development.

Within the military, the term *force readiness* describes how ready a military force is to execute its warfighting mission. Competency-based learning provides a granular look into force readiness, providing senior leaders insight into where they need to invest their developmental resources. Prior to World War II, the U.S. Marine Corps correctly anticipated the nation would face a war in the Pacific. The Corps purchased equipment to effect beach landings; however, there was also a corresponding need to teach Marines to fight in this extraordinarily challenging, sea-to-shore environment. In essence, the Corps determined a new competency was required, assessed the developmental need this new competency created (gap analysis), then began training Marines to execute the new mission.

A holistic look at workforce, student, or military-unit competencies can help leaders make learning investments more wisely

Summary

As noted at the beginning of this chapter, competency-based learning isn't new. It is, however, an exciting way to approach learning. The power it gives to learners—the control they have over their own learning journeys—creates an excitement both for the learners and those guiding them to their eventual goals. Competency-based learning also fosters creativity as both learners and leaders seek new ways to attain and demonstrate mastery. Lastly, competency-based learning offers that "common currency" that permits learners, workers, and their institutions to both understand developmental needs and to share achievements across institutional barriers.

CHAPTER 14

SOCIAL LEARNING

Julian Stodd and Emilie Reitz

Formal learning is a story written by an organization and addressed to its people. Social learning, in contrast, is a story largely written by the learners, themselves. It's about tacit, tribal, and lived wisdom that exists within distributed communities. It's often untidy, diverse, and deeply personal, as people bring their own perspectives and experiences into the learning space. Modern organizations are increasingly interested in how to unlock the power of social learning. This chapter explores that question; it describes what social learning is and elucidates a design methodology of *Scaffolded Social Learning*.[1] This is considered against the backdrop of the Social Age, the evolved reality within which we live, and an understanding of the impacts this has on learning through its forms of power, knowledge, and control.

Living and Learning in the Social Age

Technology is the most visible manifestation of change we see around us: the rise of social collaborative technologies, leading to the proliferation of connectivity, and the democratization of organization at scale. Put simply, we're now connected in many different ways, almost all of which are outside of the oversight or control of any formal organization or entity.[2] In network terms, there's high resilience and great redundancy in our connections—which is significant. Historically, mechanisms of connection were local and tribal, or large-scale and formal. We connected within formal hierarchies and formal organizations, and within those spaces, we were expected to conform, to wear the "uniform," use the appropriate "language," and accept the imposition of

"control." Today, our global connections—our connections at scale—are broadly social, distributed, and with the imminent proliferation of synchronous machine translation, often culturally diverse. We're substantially liberated from language, time, and place. And with these changes comes a shift in individual expectations, feelings of entitlement, and perceptions of fairness.

In turn, this leads to a shift in power across individual and collective and formal and informal dynamics. There's a broad rebalancing taking place around the world, slowly draining power away from formal systems (hierarchy) and into social ones (community). An important part of shifting power dynamics is the fracturing of the social contract between individuals and organizations. The notion of "career" is evolving; it no longer emphasizes lifelong loyalty between an employee and a company. Instead, our public reputations, our personal networks, and the broader communities that surround us become our "job security."[3] This has broad implications for learning and development.

In the Social Age, learning is increasingly dynamic, co-created, and adaptive, and we must invest in that co-creation

As our commitment to formal organizations becomes increasingly transient and transactional, we're seeing new entities emerge, or adapt, to fill gaps in adult education, vocational training, credentialing, and other talent management functions. Many of these entities are socially moderated and utilize social learning approaches. We already see early stages of this: Into this void step the MOOCs (democratized teaching), the tech entities such as LinkedIn and Udemy (democratized, beyond formal control), and portable credentials such as the Open Badges initiative. Looking ahead, we're also seeing new "guilds" emerging.[4] These guilds hold emergent political powers across institutions, and rather than being constrained by traditional structural organizational boundaries, they're instead defined by the bounds of knowledge and capability, such as cybersecurity or anesthesiology.[5]

Social learning is a type of informal learning; it's frequently experiential and often facilitated by distributed communities. It's generally untidy, diverse, and deeply personal, as people bring their own perspectives and experiences to the learning.

The type of learning these new entities offer is different. No longer hindered by decades of organizational stagnation and "known knowledge," it's typically more dynamic, co-created, contextual, adaptive, and free. This speaks to the challenge of how organizations need to adapt to the new ecosystem: Clinging to old models of organizational design (nested power structures), formal learning (learning as a form of control), formal hierarchies of power (systems of consequence), and known knowledge (unchallenged, static organizational dogma), is a sure fire way to be disrupted, from the level of organizations up to the scale of nations, themselves.[6] And hence, the old structures of formal power are ceding some of their relevance—unless they can adapt.[7]

We're used to seeing training and education as discrete parts of a stable system, but today, in the context of the Social Age, learning and development are dynamic parts of a dynamic system—and we must adapt them to fit the changing times, not just the new modes of delivery available. In other words, our adaptations must fundamentally readdress the design, facilitation, assessment, and support of learning. We must develop new methodologies for learning, and invest heavily in the communities and social leaders who will deliver these new capabilities so that we don't simply survive—but thrive, and avoid disruption and failure, in the Social Age.

The New Nature of Knowledge

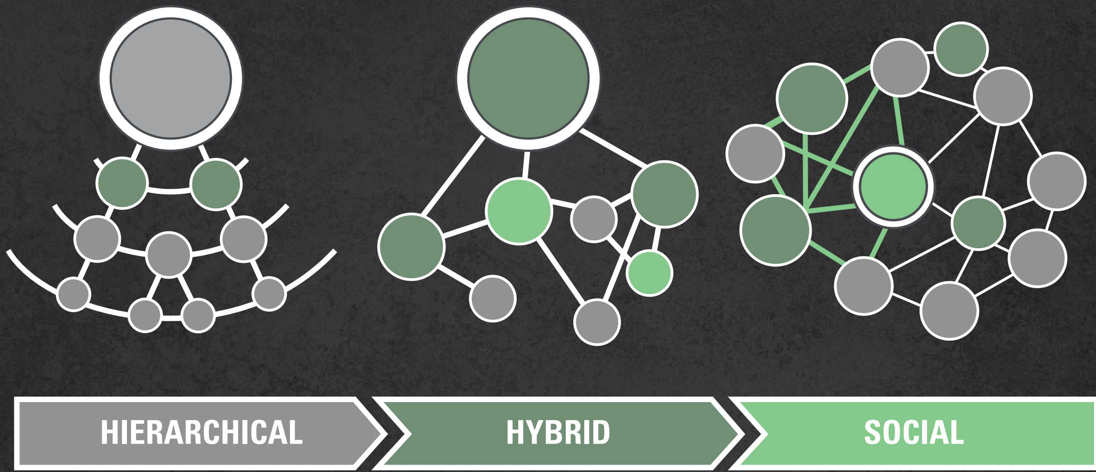
Delving into semantics may kill us, but let's briefly consider the nature of *knowledge*, not at the deepest philosophical level but at the rather mundane

and practical one: Our ways of knowing are changing. We've moved from "concentration" to "distribution." Where once we memorized and codified knowledge, and held it in libraries, books, vaults, and experts (in concentrated "centers of learning"), today it's dispersed, distributed, and free—yet, not without its problems (validity, bias).

Clearly, we still need "formal" knowledge with its mechanisms of validation, replicability, and rigor. But in many cases, we seek just enough and just "good-enough" knowledge to get us to the next step of the journey, like the information we access from our smartphones while racing through the airport, let's say, trying to make a swift decision about our connecting flight. Another key difference between formal learning and social learning is that "formal" is often abstract and frequently decontextualized while "social" is inherently applied, because it's done in the everyday reality. Where formal learning often takes place in special spaces (classroom, laboratories), social learning more often occurs in performance settings (around the water cooler) or at the point of need (a YouTube "how to" video or Reddit answer).

Is this type of distributed, community-moderated knowledge always correct? Absolutely not, but to be fair, neither was all of our "old" knowledge. And crucially we're still creating the mechanisms of validation for social knowledge that may make it ever better. This is a feature of the Social Age that's often misunderstood: What we see around us today isn't the end state. It's often the first early prototype. In contrast, the old system is relatively evolved and static. The new one is still in constant motion; it's always improving.

If we worry about validity to the point where we take no action, then we can't benefit from social learning. Conversely, if we liberate social learning with no account of the risks, we'll be overtaken by it. We must learn to balance both, in a persistent ***dynamic tension****.*



1 Learning is changing

Against the backdrop of the Social Age, the type of knowledge we engage with everyday has changed, often co-created, geolocated, adaptive, and hidden within our social communities.

2 Scaffolded social learning can support social learning

Scaffolded social learning is a design methodology, and modality of learning, which creates a loose structure, a scaffolding, within which learning communities carry out “sense making” activities, all the while engaging with both formal and informal social knowledge.

3 Learning isn’t confined to formal or controlled structures

A significant amount of learning takes place outside of formal structures and within communities that are trust-bonded, complex, and powerful. Our challenge is to create the conditions for these communities to thrive.

4 Stories fuel social learning—and can benefit those willing to listen

Within these communities, learners create stories, narratives produced both individually and collectively; these stories can inform the wider organization, if it has the humility and willingness, to learn from them.

5 Social learning is just one part of a larger, Social Age strategy

Adopting social learning is just one part of a wider cultural transformation, and that transformation could break every other part of an organization.

Some principles of social learning

In a recent research project from a healthcare setting, we (this chapter's authors) asked learners which technologies they use to collaborate. They identified 17 different platforms, only one of which was sanctioned for official use by their organization. Knowledge has already flown the coop; denying the change won't prevent it. Instead, we must engage to help better the rapidly evolving social system.

Formal and Social Systems: Dynamic Tension

The formal system is everything an organization can see, own, and control. Formal systems are where we create formal learning, and they're extremely good at certain things: collectivism, consistency, and achieving effects at scale. Flowing around and through the formal system are social systems. These aren't held in contractual relationships but in trust-based ones. The social system is multilayered, contextual, often internally conflicted, and ever changing. Social systems are also good at certain things that formal ones aren't: They're good at creative dissent, gentle subversion of outdated processes, questioning of systems, radical creativity, social amplification, movement, momentum, curiosity, and innovation.

Healthy, modern organizations exist in a "dynamic tension" between the two, and social learning takes place at this intersection, incorporating parts of the formal and parts of the social. Our challenge is to maintain, not deny or destroy, this tension.[8] If the formal system triumphs, we get greater consistency and hear the story that the formal organization agrees with, but we may not achieve true learning. If the social system wins, and subverts formal structures entirely, we lose our ability to validate quality, have consistency, and achieve effectiveness at scale. But if we can master both, we can thrive: formal structure and social creativity held in a dynamic tension. To do so requires a scaffolding, an evolution of mindset, and a willingness, on both sides, to listen and learn.

FACILITATING A SOCIAL LEARNING CULTURE

1. Create the conditions for effective social learning

Authority within formal systems is represented by rank, title, and formal qualification. In social systems, authority is granted by the collective based upon reputation, trust, fairness, and the investments made over time. It's this social authority that we draw upon within social learning communities; it's reputation that counts. In the context of social learning, our ability to learn and collaborate socially depends partly on our social authority as well as our levels of social capital. Much like we need political skills to thrive in formal spaces, so too do we need social skills to thrive in informal spaces. Self-regulated learning abilities, as described in Chapter 15, are also critical. Hence, as we think about ways to enable social learning, it's important to consider how to foster productive communities as well as how to support the social and learning processes of their various members.

2. Scaffold formal, social, and individual learning

Consider an approach for social learning called *Scaffolded Social Learning*.[9] It's a methodology for the design, delivery, facilitation, and support of this type of co-creative learning. It defines principles related to co-creative spaces, formal learning assets, and learning community support structures that help formal organizations integrate social learning into their contexts.

First, consider that in social learning, individuals will engage with formal assets (stories written by the organization, codified and accepted knowledge), social assets (tribal, tacit knowledge, held within the community), and individual knowledge (worldview, preconceptions, biases, and existing knowledge).

FORMAL LEARNING

Organizations capture their codified strength in formal stories

They share these stories through formal learning

They use technology for distribution, assessment, and compliance

GREAT FOR DRIVING CONSISTENCY, VALIDITY, AND STANDARDIZED STRENGTH AT SCALE

Social LEARNING

Communities take the formal story and add local and individual context

They carry out sensemaking activities

We can create spaces and provide support for this to happen, using scaffolded social learning approaches

GREAT FOR BUILDING DIVERSIFIED STRENGTH, RADICAL CREATIVITY, AND INDIVIDUAL CAPACITY

From a design perspective, one can, for example, vary the amounts of formal knowledge provided, create conditions for sharing tribal knowledge, and schedule reflective opportunities for individuals to explore their own experiences. The "scaffold" in Scaffolded Social Learning represents these structures. In other words, this scaffolding supports specific activities designed to facilitate and integrate formal, social, and individual learning, and to help people "make sense" of it all, both individually and collectively as a group.

Second, at a technical level, consider the implementation of Scaffolded Social Learning. It involves choreographing experiences across these formal, social, and individual constructs. Like a good play, learning can be sequenced into a "running order," so that formal learning assets are released at certain times that coincide with community activities, such as group storytelling. To extend the theater metaphor, scaffolded learning also involves a range of supporting roles, both front of stage and back of house, such as community managers, storytellers, coaches, and social leaders. These learning facilitators help define the learning spaces, encourage activities that provoke and support the manipulation (the processing) of new knowledge, and create opportunities for people to bring in and demonstrate their own specific expertise. These actions help manage the learning tempo, maintain its momentum, and drive up engagement.

3. Use gentle learning interventions to nurture social learning communities

Specific co-creative behaviors can enrich the activities of a social learning community. For instance, putting loose structure into conversations and creating common patterns of activity can help to draw out coherent narrative threads across concepts. As an example, consider the social learning tactic of *curation*. In Scaffolded Social Learning, the learning facilitator might not bring a formal example of, let's say, good teamwork or effective problem-solving, but rather would encourage learners to bring their own. Now, one person

may bring an example that seems terrible to others, and another person might offer one that seems off-track. Hence, another step is to encourage the co-creative behavior of *interpretation*. This is where someone writes a narrative, shares a story of precisely why he sees the case study as relevant or how it relates to her personal journey. In other words, this involves interpreting the thing they curated and exchanging stories across the community.

Will we agree? Well, that doesn't matter: Social learning isn't about conformity and agreement; it's about broadened understanding, context, and perspective. We don't get to deny the validity of others' examples, but we're absolutely allowed to challenge and engage in debate about them. Indeed, *challenge* can be another co-creative behavior: I tell a story, you respond, I try to paraphrase your story, you respond, we both collaborate and respond to a third story, and we come together to co-create an overall narrative.

4. Assessment is feasible, but don't apply it blindly

Our effectiveness as social learning designers is largely tied to our ability to define and master the usage, combination, and creativity of co-creative learning approaches, and to use them to craft engaging and effective learning spaces together. However, it's worth saying that organizations can measure the effectiveness of social learning equally as well as they can measure the effectiveness of their formal training and education programs (although with the caveat that that's not saying much!). Like with formal learning, it's generally worthwhile to triangulate assessment approaches:[10] Do learners feel they've learned? Does the community believe they're learning? Do learners score more highly on formal knowledge tests or in simulation-based exercises? Are there any noticeable changes to the processes or products developed outside of the learning context?

While you can technically measure anything, the pertinent question may be, *How will that information be used?* The collaborative technologies often used

to support social learning have many convenient built-in measures; various systems can report metrics about "engagement" (used as a byword for "clicking") or "interaction." They can also produce social network graphs or output all manner of frequency statistics (e.g., log-on averages, average number of posts). Technology certainly allows us to measure, but hard thinking should be done on what to measure, how to best measure it, and what to do as a result. Unless we can answer these three questions clearly, it's best not to measure at all. Measurement is enticing and important, but when misapplied, it can lack value, waste resources, and even impede learning. The best advice is to consider measurement carefully. Focus on outcomes, and where applicable, triangulate among (1) self-assessed, (2) observational, and (3) formally moderated measures.

5. Build social learning spaces and foster communities

At the heart of social learning are the learning spaces—the places people come together to carry out collective sensemaking activities. To be very clear, *space* means something very different than *community*. Consider the analogy of building a new town: You can build houses, landscape gardens, construct a mall, and pave a town square. You can even move people into those houses. But none of this creates the community. It's only begins to emerge when two of those people come together, on a street corner, let's say, and have a conversation about what a terrible job you've done on the brickwork. The buildings form the *space*; the conversation forms the foundations of the *community*. Spaces for social learning might be a classroom, a chatroom, or some kind of learning management system—however, none of those are the community.

In social learning, as in our allegorical town, individuals interact across multiple spaces, on the street corner, at the marketplace, or in someone's home. In a learning context, multiple spaces—multiple technologies—may support a community, and their conversations may span across them, starting in one

A well-designed Scaffolded Social Learning experience will contain differentiated **learning**, **rehearsal**, and **performance spaces**

and graduating to another. It's useful for the design of social learning spaces to takes this into account and to explicitly design for different types of social interactions, such as conversational spaces, collaborative spaces, infrastructure spaces (for formal components), subversive spaces (to complain about the "brickwork"), assessment spaces, and so forth.

Each learning space is differentiated by notions, such as its *permanence* and *consequence*. For example, a conversational space needs high impermanence, while a formal assessment one may carry great permanence. Collaboration spaces should be low consequence, and performance spaces may carry high consequence. Social learning takes place across these diverse constructs and associated technologies—it's not bounded by a single system or conceptual frame. Hence, the ability to construct such spaces as a coherent ecosystem is a core skill for *socially dynamic organizations*, i.e., organizations adapted to benefit from social learning approaches.

To encourage social learning communities, we need to create the conditions for them to emerge. Start by dedicating time to growing the community prior to moving into any formal learning activities. Before you can be purposeful, you need to be coherent; that is, before meaningful learning can begin, you first need to establish a high functioning community.

SENSEMAKING ENTITIES

Coherent communities are sensemaking entities; they help figure out information, identify misinformation, determine value, and recommend responses. Our social communities help us to filter the signal from the noise, and then to

understand those signals. In the context of social learning, where much of the sensemaking is done in the community, this helps provide a diversified view, and the more diverse in worldview, experience, cultural profile, and capability the community is, the more effective its sensemaking can become.[11]

MECHANISMS OF ENGAGEMENT

Within formal systems, we're assigned roles by the organization, but in social systems, our roles are more nebulous and change more often. Sometimes we bring specific expertise, resources, or capability; sometimes we bring challenge, sometimes support, and other times we're cross-connectors, linking different communities. Sometimes we simply come to learn. When considering social learning communities, it's worth remembering that we don't need everyone to engage in a certain way; we just need broad engagement. It's fine for people to take diversified roles.

RITUALS AND CHOREOGRAPHY

There's a role for ritual; in our own research, people described the "rituals of welcome and engagement" as the single most important factor for their future success within a community. Such rituals are something within our control; when designing the scaffolding for social learning, we can actively design rituals or consciously adopt existing ones. We can work with community members on their rituals of engagement for new members, for example, and can work with their formal managers on the rituals they'll use to share stories of their learning back to the rest of their teams.[12] It's all part of the choreography of learning. This means we pay equal attention to every part of the learning experience, from the email that invites someone to join to the registration instructions they receive, the way we thank them for sharing stories, and the ways we graduate them at the end. It's important to script and craft each part as an element in the overall running order. Pay attention to them all. Together, rituals and choreography form a powerful tool of community-building and, ultimately, of learner engagement.

We belong to many different communities. Some communities are visible to both us and the organizations we work for, while others are hidden deep in our social networks, out of sight from formal institutional authorities but still very relevant and connected to us individually in our day-to-day.

HIDDEN COMMUNITIES

We'll never find all the communities within an organization. Some (like our learning communities) are visible and formally sanctioned, others exist outside our networks and experience. Some even exist in active opposition, deliberately hidden from us. When we ask people what their most valuable communities are, for learning, they often speak of these hidden communities, formed on WhatsApp or as Facebook groups—places beyond formal oversight and consequence. It's worth remembering that hidden communities aren't new; we've always existed within a web of communities, but in the context of the Social Age, the boundaries between formal and social communities have blurred. Although formal communities haven't substantially encroached beyond their organizations, social ones have invaded that previously sacrosanct space. The difference today is that these hidden communities can form and operate, at scale, and do so right under our noses. This is the consequence of the democratization of communication and connectivity.

SANCTIONED SUBVERSION

Moving ourselves beyond a binary understanding of which answers are "right" or "wrong" is valuable. Sometimes the answer lies in breaking the question. Subversion itself can be of great benefit to formal systems, if they're willing to listen, because established organizations are typically very bad at subverting (or evolving) themselves. Consider this: How many organizations put as much time and effort into deconstructing redundant process and un-writing outdated rules, as they do into forming new ones? Very few! What happens around

this organizational detritus? Typically, it's subverted; people work around redundant systems and suboptimal process. And they do so not only individually, but collectively too; indeed, when people join a new organization, much of what they learn, at the local or tribal level in the early days of a new job, comes exactly from this type of crowdsourced subversion, usually under the generic banner of "this is how we get things done around here."

Conclusion

Stories, communities, learning—these are all expressions of power, and in the context of the Social Age, power itself is evolving. As we engage more broadly and more intentionally in social learning, we'll discover that our formal power doesn't carry through into social spaces: within these learning communities, you can shout all you like, but it's social authority, reputation-based influence, and social capital that count the most. In the course of adopting social learning, we inadvertently (but necessarily) erode the power of the formal organization.

As we cultivate the social community, this newly empowered collective will demand ever greater freedom and power. If our aim is learning transformation, then this power is what will drive the change.

It's a champagne bottle to uncork with care. The balance between formal systems of control and socially moderated ones creates an important dynamic tension. When managed effectively, a socially dynamic organization can emerge, one that integrates the very best of the formal (system, process, hierarchy, and control) with the very best of the social (creativity, subversion, innovation, amplification). That's our challenge: to craft more collaborative models of learning, and to learn how to build an organizational culture in which learning can thrive both for today and through our emerging future learning ecosystem.

> Americans should have self-sovereign management of their lives. Right now, medical records are yours but not so much your educational records; you don't really control any of that info right now. We're working on envisioning what the future looks like following these guiding principles: to give each person their own destiny, balance on the supply and demand side…and put it into the hands of the ones who want to earn the competencies and credentials. It gives them the power to drive the marketplace. Currently, the providers squarely have the advantage, but we need to make it a new space where learners are empowered.

Jeanne Kitchens

Chair of the Technical Advisory Committee for Credential Engine; Associate Director of the Center for Workforce Development, Southern Illinois University

CHAPTER 15

SELF-REGULATED LEARNING

Louise Yarnall, Ph.D., Michael Freed, Ph.D.,
and Naomi Malone, Ph.D.

> Self-regulated learning refers to the thoughts, feelings, and actions some learners use to independently attain their learning goals. Self-regulated learners are metacognitively, motivationally, and behaviorally active in their own learning.

There's a growing need for continuous modes of lifelong learning to cope with the acceleration of knowledge production and flow aided by new technologies. In response, both schools and workplaces are progressing towards more independent, learner-centered forms of education and development. Potential support for lifelong learning comes from improvements in AI technologies that permit more personalized learning, and greater access to mobile and search technologies that provide ubiquitous access to information. In the workplace, trainers are increasingly using cloud-based software, augmented reality, and virtual reality to prepare workers, support their lifelong learning needs, and enable diverse collaboration methods.[1] In higher education, institutions are increasingly offering online education options and providing students with information resources and communication tools to aid their independent research and collaboration. However, despite these trends, both educators and employers report challenges with this shift towards greater learner-control. For instance, some learners have difficulty taking responsibility for their own

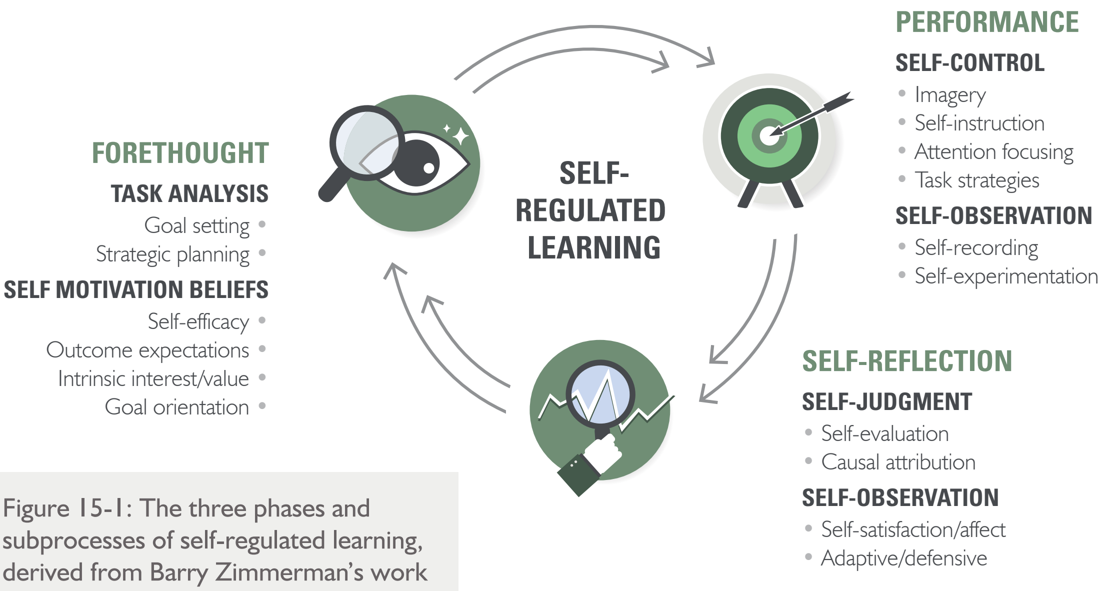


Figure 15-1: The three phases and subprocesses of self-regulated learning, derived from Barry Zimmerman's work

learning,[2] and others may struggle to assimilate their diverse experiences—leading to a situation where they have increased exposure to information but reduced overall comprehension.

Learners need to become skillful at regulating their learning over time and across different settings, especially to acquire thinking, writing, and analysis skills.[3] However, individuals often struggle to manage their learning without effective and perceptive external support, such as what a teacher, mentor, or well-structured piece of courseware might provide.[4] Consequently, developing effective self-regulated learning skills requires educators and trainers to help learners notice knowledge gaps, try new strategies, and adopt more proactive mindsets. Incorporating support for this approach into new technologies can also help learners acquire the meta-level skills needed to manage their own learning across their lifetimes.

Empirical research is beginning to identify effective tools and strategies for aiding self-regulated learning; however, the paradigm originally emerged during the 1980s when education researchers studied why some K–12 students succeeded in traditional classrooms better than others. They found the most

effective students demonstrated a set of learning strategies and mindsets including metacognitive strategies (e.g., goal-setting, self-monitoring, self-evaluation), cognitive strategies (e.g., rehearsal, organization, elaboration), environmental management strategies (e.g., time management, study area management), and self-beliefs (e.g., self-efficacy, intrinsic and extrinsic goal orientation, effort regulation).[5] Since these behaviors stemmed from learners' personal choices, researchers categorized them as "self-regulated" learning.

By the 1990s, researchers agreed that learners self-regulate during three iterative phases: the *forethought phase*, where a learner plans and initiates action; the *performance phase*, during which learning actions occur; and the *self-reflection phase*, in which a learner reflects on and evaluates performance, adjusting as necessary. Barry Zimmerman, one of the preeminent scholars in the self-regulated learning field, developed a model of these three phases, grounded in social cognitive theory (see Figure 15-1).[6]

More recent evidence has demonstrated that some self-regulation strategies—time management, effort regulation, and critical thinking—have positive impacts on academic outcomes, but that other strategies—rehearsal, elaboration, and organization—have less empirically convincing effects. Further, in both school and workplace settings, a small number of these strategies have the largest impacts, accounting for 17% of the overall variation in learning outcomes.[7] These include:

1. CONFIDENCE, SELF-EFFICACY, INTERNAL LOCUS-OF-CONTROL – Effective learners believe they can learn because they're in control and tend to take a more "active" approach to learning. By contrast, less effective learners doubt they can learn (because they think they're not smart enough or not in control) and, consequently, take a more "passive" approach to learning.[8]

2. GOAL SETTING AND PLANNING – Effective learners set appropriate learning goals, anticipate the resources required, and set benchmarks for their progress. By contrast, less effective learners may not set goals or may simply

…it's not going to replace teachers, it shifts the role and nature of a teacher to a master facilitator.

Thomas Deale
Major General, U.S. Air Force (Ret.)
Former Vice Director for Joint Force Development on the Joint Staff

plunge in, then run out of time or lack access to appropriate learning resources.[9]

3. PRIOR KNOWLEDGE AND STRATEGY USE – With stronger prior knowledge, effective learners engage in greater instances of planning and monitoring, both independently and in collaboration. With lower prior knowledge, less effective learners use just a few strategies.[10]

4. METACOGNITIVE MONITORING – Effective learners note and address gaps and misunderstandings while they learn. Less effective learners fail to notice or address such difficulties in their learning.[11]

5. POST-LEARNING REFLECTION – Effective learners consider what they've learned, taking stock of what remains to be learned. Less effective learners fail to reflect sufficiently after learning and may rush to the next task.[12]

RECOMMENDATIONS

Helping learners develop better self-regulated learning skills will require new supports, added into the many contexts where people engage in learning. To cultivate awareness of Zimmerman's three phases of self-regulated learning and to develop effective habits at the cognitive, metacognitive, emotional, and behavioral levels, we propose three conceptual levels of self-regulated learning support: micro-, macro-, and meta-interventions. The *micro-level* focuses

on individuals and the tools they use to better navigate a personalized trajectory. The *macro-level* focuses on how to navigate the selection and progression across learning experiences. At the *meta-level*, there's a recognition that building appropriate learning habits requires focused practice in the cognitive, social, emotional, and physical capabilities that contribute to resilience, effective decision-making, and lifelong personal growth. We describe applications of these three levels in the suggested interventions below.

1. Use formative assessments to personalize support for self-regulation skills and mindsets

Although research shows the benefits of supporting learners' self-regulation, these interventions often rely upon the discretion and knowledge of their educators. Hence, better supporting self-regulated learning depends, in part, on enhancing the skills of teachers, workforce trainers, and managers, in addition to learners, themselves. To start, it's useful to help stakeholders identify the specific self-regulation skills and/or mindsets needed in a given learning situation; a first step towards that is to translate self-regulated learning assessment methods from research into practice. For instance, several diagnostic tools can help identify the signs and symptoms of a learner with weak self-regulation mindsets or strategies. These diagnostic tools could be embedded into online courseware or used by teachers, trainers, and learners in both classroom and workplace settings.

Drawing on the three-level support approach to self-regulated learning: Tools can be devised to support individual educators in learning specific diagnostic techniques (*micro-level*), to help them anticipate where self-regulated learning challenges may occur before any extended learning activity (*macro-level*), and to serve as a regular formative assessment to encourage the maintenance of effective mindsets and habits of self-regulated learning (*meta-level*). Below are some self-regulated learning assessments that could be put to use:

SELF-REPORT INSTRUMENTS

Technology can deliver self-report, self-regulated learning assessments; the results from these may be shared with teachers and trainers or fed into adaptive learning algorithms to provide more personalized support to learners. Such assessments may target key elements known to support self-regulated learning, including: level of motivation (e.g., *The Motivated Strategies for Learning Questionnaire*[13]) and the skills of goal-setting, time-management, help-seeking, preparing the study environment for focused work, and self-evaluation (e.g., *The Online Self-Regulated Learning Questionnaire*[14]).

ASSESSMENTS IN ACTION: GOVERNMENT WORKFORCE EXAMPLE

In Marcus Buckingham's work, *StandOut*, he designed an assessment…

One of the things that he applied there—that's extremely successful—is a weekly check-in with a supervisor. Once a week, through technology, it sends a request: *These were your goals last week. Were you able to reach these goals? What are your new goals? Did you use your strengths? What did you like? What did you detest?*

Responses help the supervisor know things like, *John keeps disliking this, and I need to get this off his plate and make it less painful for him. This is what he's liking, where he's using his strengths. I need him to do more of this.* It allows for side questions, too, like, *how motivated are you in what you do? How are you as an employee in working with this environment?*

Then there were 5 critical questions provided quarterly asking if the team is growing and learning. It's a huge help for a leader, and it also prompts me to go in and say, "This is what John is working on. This one's important, so can you put it at the top of your list? Thanks for the great idea; I'm glad you're working on it." These learning interventions cause us to have a conversation in a less threatening format and talk back-and-forth. There are lots of benefits and these are the kinds of interventions we intend to apply during the Leadership for a Democratic Society.

Suzanne Logan, Ed.D., SES
Director of the Center for Leadership Development and Federal Executive Institute, U.S. Office of Personnel Management

* applied example

STRUCTURED INTERVIEW PROTOCOLS

Drawing from questions in existing research interview protocols, technology can be adapted to deliver helpful queries to teachers and trainers. These may, for example, help them consider and investigate the potential factors contributing to weak outcomes, either observed among students in school or personnel in a workplace setting. Factors useful for reflection include assessing learners' skills for organizing and transforming information, setting goals and planning to learn, seeking information, keeping records and monitoring learning progress, preparing their study environment for learning activities, engaging in self-evaluation, meting out self-consequences, reviewing texts and notes, help-seeking, and rehearsing and memorizing. (See, for example, the *Self-Regulated Learning Interview Schedule.*[15])

MEASURING SELF-REGULATION PROCESSES AS EVENTS

Education technology researchers working primarily in learning management systems are already moving towards designing more complex, process-oriented measures that can determine individuals' deployment of self-regulated learning strategies over time. Measurement methods include think-aloud protocols and technologies that detect errors in tasks or employ online trace methodologies (e.g., of mood and task steps) that measure individuals as they go about their learning activities.[16] To better support self-regulated learning, researchers will need to study how to adjust these types of detection methods for delivery and use across different learning technology platforms, such as mobile, augmented reality, and virtual reality.

2. Build confidence, self-efficacy, and internal "locus of control" about learning

To realize a vision of self-regulated learning across a lifetime, more needs to be understood about the preconditions for developing habits of lifelong

learning. International studies indicate wide variation in how well both early childhood education and family upbringing sets the stage for lifelong learning;[17] however, it generally begins with establishing confidence and independence as learners. Over the past 35 years, K–12 education researchers have found evidence that open-ended instructional practices, such as guided inquiry activities, foster confidence and independence in learning more than other practices, such as traditional close-ended question-and-answer routines.[18] Introducing open-ended practices in childhood can help set the conditions for lifelong learning, but continued support for self-regulation is needed even in adulthood. For example, some research indicates that those countries with the highest levels of lifelong learning among adults have robust adult education systems.[19]

Based on the three-level support approach to self-regulated learning, described at the beginning of this section, individual educators can be tutored in confidence-building techniques (*micro-level*); in methods for identifying likely areas of low confidence in an upcoming lesson (*macro-level*); and in noting, reflecting on, and accepting their own challenges with maintaining confidence during learning (*meta-level*).

> The one point I hope every single person can internalize—as the neuroscience evidence shows us—**the brain is learning every single second of every single day**. So, the way every individual learns is the same, but what they're learning differs and that depends on context—internal and external. Our job is to align our learning goals to what the brain is actually learning. That's a big paradigm shift for leadership.
>
> **Melina Uncapher, Ph.D.**
> Director of Education Program, Neuroscape; Assistant Professor of Neurology, Weill Institute for Neurosciences and Kavli Institute for Fundamental Neuroscience, University of California San Francisco

3. Develop goal-setting and planning skills

To improve self-regulated learning, goal-setting and planning, strategies should be translated into user-friendly tips to guide individuals while they learn. Such self-regulated learning support should be made available across a range of learning contexts, from face-to-face to online environments. The three-level support approach to self-regulated learning is useful here, too. Individual learners and learning facilitators can be linked to templates and tools to support goal setting and planning (*micro-level*). They can be encouraged to reflect on the pacing and time management required in multiple stages and phases of upcoming lessons and projects (*macro-level*), and they can be encouraged to confront resistance to goal setting and planning by seeing the success stories of those who employ these techniques regularly (*meta-level*).

4. Activate prior knowledge to enrich self-regulated learning strategy use

Past education and experience represent both a potentially rich learning resource and a possible threat, since old habits and misunderstandings can block the grasp of new ideas and procedures. For this reason, educators, trainers, and instructional designers should incorporate activities and tools to elicit learners' prior knowledge and help them reflect on which elements of it are potential building blocks and which are possible barriers.

Based on the three-level support approach to self-regulated learning, ways for activating prior knowledge might include: Linking individual learners and learning facilitators to lessons about how to elicit and document prior knowledge relevant to a particular lesson (*micro-level*). Identifying the useful prerequisite knowledge as well as the naïve concepts that might pose learning hurdles in upcoming lessons or projects (*macro-level*), and supporting individuals' capacity to activate useful prior knowledge and to counter or encapsulate less useful prior knowledge (*meta-level*).

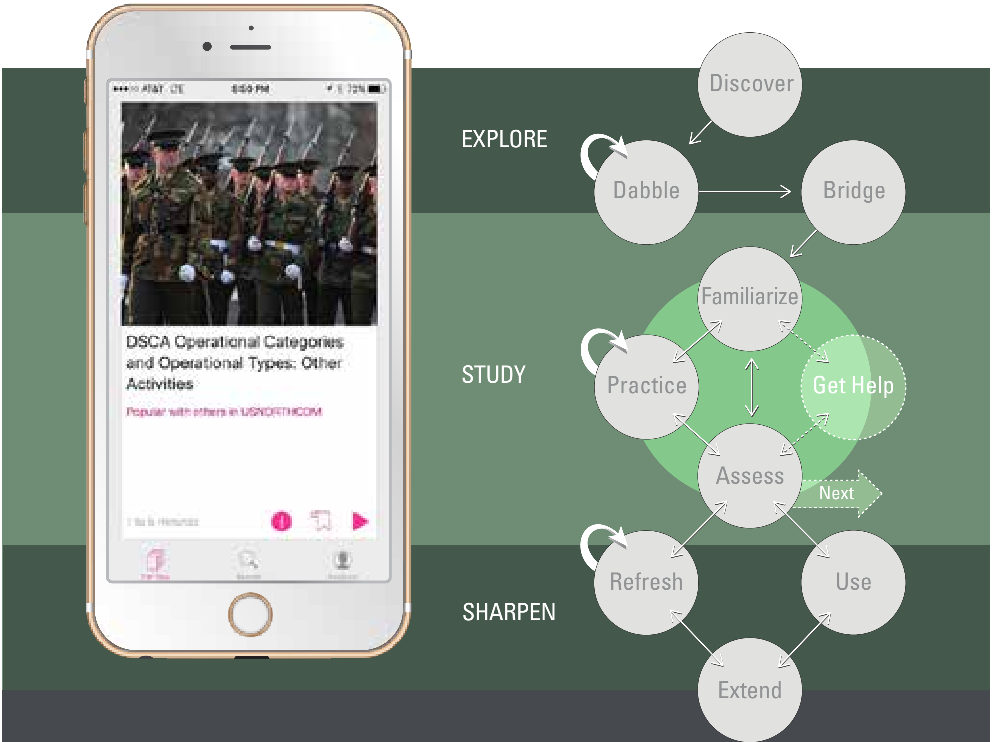
> …it's not just what you learned but rather how much it **changed you**.
>
> **Betty Lou Leaver, Ph.D.**
> Director, The Literacy Center; Manager, MSI Press; Former Provost, Defense Language Institute Foreign Language Center

More research is needed in this area, however, to uncover new methods for estimating learners' prior content knowledge and self-assessed self-regulation skill levels. Since traditional testing can negatively impact learners' motivation, finding new assessment methods is a critical step to enhancing personalization models beyond their current level. Currently, traditional testing approaches and curriculum sequences favor comprehensiveness and certification. Work is needed to understand how adjusting the frequency and forms of assessment can inspire rather than hinder self-regulated learning. Methods worth exploring include integration of self-reflective assessments of content knowledge and self-regulated learning skills with validated measures of traditional content knowledge and skills.

5. Support metacognitive monitoring

As learning platforms and media proliferate, the community will need a wider range of ways to gather trace data on how and under what conditions learners use self-regulated learning supports. This line of research is likely to innovate around new approaches to using xAPI to collect student data, usefully aggregate datasets across experiences, and apply learning analytic models to analyze them. Such work need not focus only on individual learners' patterns, but should also consider patterns within content pathways from multiple users. Such data traces can support more personalized and optimal recommendations of what content to review next and can strengthen systems to covert-

PERLS app



U.S. DEFENSE TECHNOLOGY EXAMPLE

By providing fast access to short-form learning materials ("micro-content"), mobile applications can make it easy to use brief windows of available time for learning. Such applications can use AI to identify high-interest topics, select learning activities most likely to benefit the learner, and then recommend micro-content on selected topics and activities. For example, PERLS, a mobile app developed with DoD support, presents recommendations in the form of electronic cards that users flip through to find preferred content, and underlying these recommendation is a dynamic model of self-regulated learning. The app has been evaluated with several DoD organizations, including U.S. Northern Command and Joint Knowledge Online to augment training in areas such as Defense Support of Civil Authorities. Early results show that learners using PERLS reported heightened enjoyment and motivation to learn, and they performed as well as others required to take a full, formal courses.[20]

> If we believe that the exploration of knowledge must continue, then we can't only teach the knowledge we currently have. Truth and facts are constantly unfolding. If we just decide that by 2018 we have all the knowledge we'll ever need then we're making a serious mistake.
>
> **Christopher Guymon, Ph.D.**
> Interim Dean of the Graham School, University of Chicago, Office of the President

ly strengthen or fade self-regulated learning support in a continuous fashion.

One aspect of self-regulated learning support that has not been adequately studied concerns understanding both the optimal *frequency* of self-regulated learning support and the optimal *tools* for providing this support. These factors are likely to vary by the content to be learned as well as the learning platform (e.g., LMS, mobile smartphone). R&D developers should be prepared to make the case for which self-regulated learning skills they plan to target, highlighting those skills most important for learners of their content and most amenable to support with their particular learning experience. Such design specifications can improve the field's understanding of how different technologies can support specific self-regulated learning skills.

Supporting metacognitive monitoring across the three levels of abstraction might include: Connecting individual learners and learning facilitators to tips and guidelines for noticing and remedying points of confusion, poor procedure or technique, and weak understanding (*micro-level*); identifying points for checking on understanding and procedures in upcoming lessons and projects (*macro-level*). Additionally, new methods may be able to track progress over time, measuring the effectiveness of techniques in reducing misunderstandings and, in turn, providing systematic feedback that sharpens procedures over time (*meta-level*).

6. Foster habits of post-learning reflection

Educators, trainers, and instructional designers need to provide extended post-training self-regulated learning support for learners, helping them to reflect, learn how to reinforce, and know when to refresh past learning. Such post-training support could be delivered by mentors and coaches, aided by the parent organization, or take the form of persistent technology-based tools for self-coaching and reference.

To return once again to the three levels of abstraction, ways to foster post-learning reflection might include: Providing lessons to individual learners and learning facilitators about the kinds of useful questions to pose (*micro-level*); scheduling and building-on reflection activities across an extended lesson or project (*macro-level*), and rewarding learners for engaging in reflection activities, such as offering them the chance to unlock a range of new learning opportunities based on their reflective participation (*meta-level*).

Summary

Successful self-learners do more than just study and memorize. They stay alert and are curious to discover new, valuable learning. They skim a lot of content to find the important points. They search informally to nurture motivation for intensive study and periodically review afterwards to fight forgetfulness. *And they find the time to do it all.*

Though more than 70% of work-related learning is self-learning, few technologies help self-learners deal with these challenges. Ideally, technology will reduce the difficulty and friction of all self-learning activities, while making it easier to learn in small slots of available time, whenever and wherever these occur. Targeting and supporting self-regulation skills throughout personalized learning trajectories will aid learners of all ages and promote enhanced learning efficiency across lifetimes.

Organization

> “In an era where gaining access to information is no longer difficult, a continuing culture of high-stakes testing (focused on testing knowledge recall) runs counter to what we need. We should instead value the ability to sift through information and to connect, assimilate, aggregate, interpret, and apply data. If our teachers could help students view information from societal, cultural, economic, and other perspectives, and if they could help students practice writing and data-validation skills and creativity, we could accomplish so much more than just teaching them how to answer multiple-choices tests.

Anne Little, Ph.D.

Vice President, Training Solutions Development, SAIC

CHAPTER 16

INSTRUCTIONAL DESIGNERS AND LEARNING ENGINEERS

Dina Kurzweil, Ph.D. and Karen Marcellas, Ph.D.

For over 60 years, instructional designers have supported teaching and learning, primarily by identifying effective ways to present material in formal educational and training environments. Given advances in technology, increasing access to data, and the explosion of formats and venues for learning, designers in the future will have to gain more knowledge and expertise than ever before as they develop their professional craft. Consequently, a new concept is entering this complex field: the learning engineer. Who are these individuals? What are their areas of expertise? How do their knowledge and skills relate to, expand upon, or differ from those of instructional designers? This chapter describes the history of instructional design and explores how the field of learning engineering will need to develop and expand upon instructional design methodologies to support teaching and learning in the future.

Background: Design of Instruction

Traditionally, a number of specialists have collaborated in developing learning experiences and tools. Their titles and roles may differ somewhat depending on the project or the available personnel, but one commonly used team structure includes a technologist, a learning science expert, and an instructional designer. Technologists generally have technology backgrounds and use either personal experience with education or some learning science knowledge to help develop instructional technology tools. Some certainly have robust

educational knowledge, but usually this isn't the norm. In contrast, learning scientists are educational researchers who are deeply knowledgeable about how humans develop and learn, particularly from a cognitive perspective. Both of these roles can act in support of instructional designers, who apply a systematic methodology based on theory, research, and/or data to plan ways to teach content effectively. Instructional designers work in both educational and training environments. They're problem solvers who use different instructional models to promote learning. In other words, they're responsible for "the theory and practice of design, development, utilization, management, and evaluation of processes and resources for learning." [1]

A BRIEF HISTORY OF INSTRUCTIONAL DESIGN

The field of instructional design is historically and traditionally rooted in cognitive and behavioral psychology. It first emerged during a period when the behaviorist paradigm dominated American psychology. Its practice can be traced back to the late 1950s and early 1960s, but in those early days, one wasn't referred to an "instructional designer." Rather, those who worked in this field were typically called educational psychologists, media specialists, or training specialists.[2]

Through the 1960s and 1970s, the growth of digital computers influenced learning theories, and many new instructional models adopted an "information-processing" approach. The 1970s also heralded the systems approach to instructional design, including one of its best-known models, the Systems Approach Model, published by Walter Dick and Lou Carey.[3] The Dick and Carey approach offered a practical methodology for instructional designers, and it emphasized how each component of the model works together. Dick and Carey also highlighted how technology, media, and research were all impacting the field at that time and, consequently, how "modern" instructional designers differed greatly from their counterparts in the 1960s in terms of academic background, training, research, and tools.[4]

EXAMPLE: The proliferation of video cameras makes it possible for any instructor to record videos for use in courses; the role of the instructional designer is not simply to facilitate the incorporation of video but rather to examine instructional goals and identify areas where it can be used most effectively to support student learning, while also possibly identifying appropriate use of lower-technology and lower-bandwidth solutions in other areas. They also work with faculty to define content that would best be suited for video. Continuing with the video example, instructional designers also look at the video's effect on learning and develop ways to improve the both the product and the learning outcomes.

Throughout the 1970s and 1980s, the instructional design field continued to evolve; a later survey of instructional design models found they had differentiated into having a classroom orientation (focused on development of instructional materials for a single lesson or set of lessons by teachers), a product orientation (focused on development of specific products by teams), or a system orientation (focused on development of curricula by teams).[5] Present-day instructional design continues to have different application specialties, and it continues to be influenced by technology. However, rather than model instructional design theories on technology, as in the 1960s and 1970s, contemporary instructional designers explore ways to incorporate technology into their work.

Experienced instructional designers recognize that technology has numer-

ous uses for learning—but it's still just a tool. While technology can provide many benefits, its effective use in training and education requires carefully defining its role and ensuring it remains subordinate to the learning goals. In recent history, we've seen a push for instructional designers to focus more on technology, shifting emphasis away from instructional theory. However, the systematic design, development, implementation, and assessment of teaching and learning requires that instructional designers keep instructional methods central to their work and examine all technology with an eye towards promoting more effective learning.

> *"Technology is not an end in itself; any successful use of training technology must begin with clearly defined educational objectives."* [6]

INSTRUCTIONAL DESIGN ACTIVITIES

Instructional designers' primary role is to support good instructional practice. As many professionals in the teaching and learning fields have known for decades:[7] Teaching is a complex activity that, when done effectively, is closely tied to the success of learners.[8]

Many times, instructional designers work with subject-matter experts, such as training facilitators, teachers, and/or other faculty members, to help them translate their content knowledge into effective learning experiences, usually for formal learning contexts. Often, these content experts have less familiarity with effective instructional practice; hence, instructional designers introduce them to key principles and help them incorporate more effective methods. Instructional designers help their clients think more critically about a range of issues related to instruction, including the needs of learners, curricula, learning environments, and associated policies.[9]

Instructional designers generally use systematic models and methods, such as the systems approach, backwards design, successive approximation model,

and the Kemp instructional design process. Their approach usually involves identifying desired outcomes and determining the skills, knowledge, and attitude gaps of a targeted audience. They apply theory and best practices to plan, create, assess, evaluate, select, and suggest learning experiences to close those gaps.[10] Instructional designers may be involved with the entire instructional process or with portions of it. For example, early in a project, they're often involved with the systematic review and critical appraisal of existing materials. Using research and theory, instructional designers may also conduct analyses before the actual instructional design and development occur. Later in the process, instructional designers may emphasize the importance of assessment and evaluation, to ensure learning experiences have met their intended goals. A common theoretical and practical understanding of innovation also contributes to instructional designers' work, and the best instructional designers ensure their clients, fellow educators and trainers, and leadership recognize how the different tools, processes, materials, and innovations that make up learning systems can enhance their learning offerings. Hence, instructional designers need to additionally have a creative spirit of design,[11] including an imaginative, creation-oriented, and interdisciplinary character as well as the creative spirit to remain flexible and perceptive in their practice. That is, despite the proliferation of formal processes, such as instructional systems design, instructional design remains an art—albeit one firmly grounded in science and theory.

A **learning engineer** is someone who draws from evidence-based information about human development—including learning—and seeks to apply these results at scale, within contexts, to create affordable, reliable, data-rich learning environments.

Bror Saxberg, Ph.D., M.D.
Vice President of Learning Science, Chan Zuckerberg Initiative

> *"Designing is a process of pattern synthesis, rather than pattern recognition. The solution is not simply lying there among the data... it has to be actively constructed by the designer's own efforts."* [12]

CHANGING CHARACTER OF LEARNING

The growth of technology and access to learner data has led to advances in learning science and made the learning environment more complex. This, in turn, affects the roles of instructional designers, who must now interact with a variety of formal and informal modes of learning, social and experiential learning theories, as well as new tools, processes, and people. This complex infrastructure has been called the "learning ecosystem." It encompasses the physical and mechanical elements of educational and training environments; the theories, processes, and procedures that drive their use; and learners' (complex) relations to and interactions within that environment. This includes all elements that make up learning, from the formal classroom and those traditional instructional activities, to the technologies used to support informal learning. The complexity of the future learning ecosystem is turning instructional design into an even more dynamic activity, where designers must be aware of how all these elements come together, how each works, and how to best orchestrate learning across time, space, and media.

These advancements have similarly transformed the expectations of leaders, educators, trainers, and learners, and at the same time, they've created an abundance of choice for anytime/anywhere learning. The strategic challenge is that, unlike when learning occurred primarily in a classroom with limited technology options, today there are many resources available in personal learning ecosystems, classrooms, training programs, and beyond. Given that

most of these new resources rely on technology, the challenge is no longer about mastering a few platforms in a constrained environment—it's about understanding the benefits of multiple resources, maintaining awareness of the wide variety of capabilities, choosing the best ones for learning, and balancing the entire ecosystem of multiple resources in a way that provides greater support overall. Such rapid advancements have made it ever more challenging for conventional training, education, and instructional practitioners to build effective strategies, tools, policies, and designs; hence, there's need for a new player: the learning engineer.

Learning Engineers

In December 2017, the Institute of Electrical and Electronics Engineers (IEEE) Standards Association Standards Board recommended creation of a new 24-month working group, called the *Industry Connections Industry Consortium on Learning Engineering* or ICICLE, to provide definition to and support for the burgeoning field of learning engineering. Creation of this group marks a groundswell of attention on the learning engineering field, although its original concept dates back to the 1960s, from Nobel Laureate Herbert A. Simon, who wrote at the time:

> The learning engineers would have several responsibilities. The most important is that, working in collaboration with members of the faculty whose interest they can excite, they design and redesign learning experiences in particular disciplines. […] In particular, concrete demonstrations of increased learning effectiveness, on however small a scale initially, will be the most powerful means of persuading a faculty that a professional approach to their students' learning can be an exciting and challenging part of their lives.[13]

Learning engineering, as conceived today, is an interdisciplinary approach based on an in-depth foundation and education in proven theoretical models and methods, educational paradigms and instructional approaches, and sci-

AI: In many ways it's solving similar problems as before but doing it more effectively with data. For example, we can search and find content with a much deeper understanding of its meaning. We can get better at questions such as: "What's the student really trying to learn? Can we find the part of a video that would be most helpful? How else can we make this experience easier for students?"

Shantanu Sinha

Director, Product Management, Google
Former Founding President and Chief Operations Officer, Khan Academy

entific and analytical methods. Learning engineers use data and knowledge of enterprise structures to help promote good decision-making in the use of learning ecosystem components. With its focus on data, and in using validated methods that put learning data to work in the service of improved learning outcomes and institutional effectiveness, this emerging field takes a step beyond traditional instructional design. Learning engineers do this, in part, by combining big data with design-based research to improve the design of learning experiences.[14] Additionally, learning engineers use theoretical and practical understanding to scale innovations across the learning ecosystem.

Learning engineers can help with the complexities of integrating various technologies, workflows, interactions, and data-driven processes to enable learning. They may engage with widely varying technologies, including learning management and learning content management systems, mobile learning

applications, course authoring tools, MOOCs, digital simulations and game environments, virtual/augmented reality, micro-credentials, learning applications and tool developments, learning records and analytics dashboards, video and other streaming content, and new applications involving wearable and IoT technologies. Though learning engineers may not necessarily write software code or serve as systems administrators, they can influence the design, development, integration, implementation, and use of a wide variety of technologies. They might, for instance, recommend AI algorithms, such as deep learning, to analyze data gathered in rich learning experiences to create a clearer picture of learners. This information can be used to inform how learning is supported, for instance, by deepening student engagement in their courses, improving the efficiency of teachers' instructional methods, or providing learning tailored to individual needs.[15]

"Bringing together teams of collaborators with different kinds of expertise—teaching, subject matter knowledge, instructional design, and data analysis—is a prerequisite for realizing the full potential of learning system data."[16]

The growing and dynamic learning ecosystem means learning engineers are likely to play much larger roles in the planning, design, development, and analysis of diverse and complex instruction. Learning engineers, like instructional designers, will be expected to anticipate changes or new developments in applicable technologies or in the instructional fields affecting their specialty areas and programs. They'll also need to continually improve their instructional strategies to reliably identify best practices and opportunities for change. Accordingly, learning engineers need to possess a wide scope of competencies, including a foundation in learning science as well as the use of data to improve learning practice. They need to know good learning design principles, be conversant in learning analytics and enterprise learning technologies, and have some unique areas of relevant expertise, such as cognitive science, computer science, or human-computer interaction.

I don't think that from a military perspective that we've completely taken advantage of large data management. Here's a great analogy: We have hundreds, if not thousands, of hours of full motion video, but how much do we actually analyze based on the current tools…? Eighty-plus percent isn't reviewed in detail. Until recently, we were working on automating that and that's one element I look at data management for—turning those mountains of data into decision-quality information.

Thomas Deale

Major General, U.S. Air Force (Ret.)
Former Vice Director for Joint Force Development on the Joint Staff

In general, learning engineers tend to focus more on technology and data-driven decision-making than do instructional designers. At the highest levels of expertise, learning engineers typically act as partners to provide leadership, advice, and guidance throughout an organization and to serve in key staff positions, such as a specialist at agency or major military command headquarters, or in a generalist capacity as an educational specialist at a school or university. Learning engineers' focus on data could give them an inroad for working with learning professionals who need grounding in assessment or in how learning works, such as training facilitators, teachers, and faculty at educational institutions. Those drawn to evidence-based practices might be especially interested in working with a learning engineer. In a higher education environment, for example, learning engineers could provide a valuable

service by helping to link research and teaching, both promoting current research into effective teaching and encouraging faculty members to conduct such research. Learning engineers can also work in many different industries, perform many different tasks at various organizational levels, and, indeed, work side-by-side with instructional designers and other learning professionals—but with a different focus.

Instructional designers and learning engineers should collaborate and partner to assess learning needs, develop strategies, and implement plans based on all the component parts and connections within the ecosystem in which learning occurs. Both instructional designers and learning engineers have valuable knowledge and competencies that can help make the most effective use of learning resources, and together, they can contribute to transforming how we think about teaching, learning, education, and training.

IMPLEMENTATION

Define the Roles

While they can work together and have some overlapping skill sets, there are important distinctions between learning engineers and instructional designers. Notably, while learning engineers' skills are grounded in applied learning sciences, they additionally emphasize data science, analytics, user experience, and applied research. Learning engineers also have a greater depth and range of experience, including some expertise in the implementation and improvement of learning ecosystems—that is, in working with diverse, technology-enabled, data-driven learning systems.

Before becoming a learning engineer, someone must acquire the highest levels of knowledge in learning theories, models of learning, data about learning, research into learning, and the management of learning. They're also likely to need higher levels of technical experience than instructional designers. As

such, unlike an instructional designer who can start at the entry level and develop skills over time, learning engineers must have more extensive educational backgrounds and prior experience. The mix of knowledge and experience, or, more specifically, the ability to filter expert knowledge through the lens of practical experience, helps characterize the learning engineering approach to instructional solutions.

To be clear, education alone won't give learning engineers the practical knowledge nor integrated experience they need to be successful. A typical learning engineer wouldn't come out of an undergraduate program; rather, we'd expect a learning engineering protégé to build upon undergraduate work in education or a relevant technical field with applied experiences and subsequent advanced preparation. For instance, someone might first train and work as an instructional designer and then later seek additional education in the research, learning sciences, and data-based problem-solving elements of learning engineering.

Education and Professional Growth

What would the education of a learning engineer look like? As discussed previously, they must have a solid grounding in learning science as well as experience with instructional design, curriculum development, evaluation, and other educational areas. They should understand statistical modeling approaches for education and training, analysis of large datasets, and the use of evidence to improve learning. Befitting the word "engineer," they also need some background in math or science, to help them identify and solve complex, sociotechnical problems in logical ways.

We must be cautious in thinking about learning engineering as simply a university degree. Learning engineering should be a cross-disciplinary program, likely at the master's or doctoral level. These programs should also be competitive. Universities should evaluate applicants for sufficient prior knowledge

and experience. Entrants into a program could have various areas of relevant expertise, and the purpose of the program would be to engage them in developing a common vocabulary, breadth of awareness, and solid ability to examine data to identify learning evidence.

A learning engineering graduate program could have various areas of focus to complement the vocabulary and data elements. For instance, a technology-focused concentration in a learning engineering program could incorporate artificial intelligence, simulation, augmented/virtual reality, intelligent tutoring systems, or UI/UX for learning. But at the heart of any program must be learning science and design. Using science and theories as guardrails is valuable for all types of learning professionals in creating engagement, establishing context, and promoting application. Though technology may be helpful in many cases, implementing technology is not the goal—good instruction and learning are the focus.

In the end, the graduate from such a program should be able to design and implement innovative and effective learning solutions in complex systems, potentially at scale, and aided by advanced technologies when appropriate. They should be able to use data and a solid, theory-based evaluation framework to improve learning and assessment in practice. Whether applied to industry, government, military, or academic settings, these graduates should bring value above-and-beyond that provided by traditional instructional designers.

Job Series, Titles, and Competencies

The path to the job of the instructional designer or learning engineer may begin with teaching in K-12 or higher education; working in technology in corporate, government, or military environments; holding an academic research position; or filling some other responsibility related to educating or training people.

Because the U.S. Federal Government has a strict classification system for employment, and because it employs so many education professionals, it

serves as a useful lens through which to view the learning engineer role. The Office of Personnel Management classifies jobs in the Federal Government, and its General Schedule outlines the occupational groups, series codes, and classifications of positions including their duties and responsibilities, descriptions, and standards.[17] Each occupational group (such as the 1700 "Education Group") is indicated by the first two numbers of a four-digit sequence, and the subspecialties in that group fall within the specified range, for instance between 0000 to 0099. The 1700–1799 occupational series covers education and training–related professions, such as "training instruction" (1712) and "public health educator" (1725). The requirements and description for learning engineering should be included within this general series.

Currently, instructional design falls within the 1750 sub-series (i.e., the "instructional systems series"). It seems like a clear solution to expand this sub-series to incorporate the competencies necessary for learning engineers and related future learning professionals. For instance, the title could change from "instructional systems series" to "teaching/learning support and instructional systems series." This would follow a trend in the industry acknowledging the importance of supporting teaching and learning, broadly. Also, more detailed language about the work performed by learning engineers, their education qualifications, and experience requirements could be added to the description. Correspondingly, the upper end of this job series should be reviewed to ensure that pay and benefits are appropriately aligned with the necessary experience and education. If we don't reframe this series (or take similar actions), it's more likely key learning engineering components will become lost within an organization or devalued in career planning or performance appraisals; we also risk learning engineers being conflated with instructional designers.

The success of the instructional designer or learning engineer of the future will ultimately rest on how institutions and their leaders connect, communicate, support, and value those specialties. Learning engineers shouldn't be seen as "one-time stops" or clearinghouse consultants for educational products.

60YC: THE 60 YEAR CURRICULUM

The dean of DCE [Harvard's Division of Continuing Education], Hunt Lambert, is leading this effort to transform lifelong learning, which is now a necessity in our dynamic, chaotic world. The 60YC initiative is focused on developing new educational models that enable each person to re-skill as their occupational and personal context shifts. The average lifespan of the next generation is projected to be 80-90 years, and most people will need to work past age 65 to have enough savings for retirement. Teenagers need to prepare for a future of multiple careers spanning six decades, plus retirement. Educators are faced with the challenge of preparing young people for unceasing reinvention to take on many roles in the workplace, as well as for careers that do not yet exist.

On-the-job learning is familiar to most adults; many of us take on tasks that fall outside of our academic training.…but our children and students face a future of multiple *careers*, not just evolving jobs. I tell my students to prepare for their first two careers, thinking about which is a better foundation as an initial job—but also building skills for adopting future roles neither they nor I can imagine now…Given this rate of change, education's role must be long-term capacity building—enhancing students' interpersonal and intrapersonal skills for a lifetime of flexible adaptation and creative innovation—as well as short-term preparation so that they are college- or career-ready. Education must also advance two other goals beyond preparation for work: to prepare students to think deeply in an informed way and to prepare them to be thoughtful citizens and decent human beings…

The 60YC initiative centers on the least understood aspect of this challenge: What are the organizational and societal mechanisms by which people can re-skill later in their lives, when they do not have the time or resources for a full-time academic experience that results in a degree or certificate? Thus far, attempts to address this issue have centered on what individual institutions might do. For example, in 2015 Stanford developed an aspirational vision called Open Loop University. Georgia Tech followed in 2018 with its model for Lifetime Education. The hallmarks of these and similar models center on providing a lifelong commitment to alumni that includes periodic opportunities to re-skill through services offered by the institution; microcredentials, minimester classes, and credit for accomplishments in life; personalized advising and coaching as new challenges and opportunities emerge; and blended learning experiences with distributed worldwide availability. I believe a possible third approach is to reinvent unemployment insurance as "employability insurance," funding and delivering this through mechanisms parallel to health insurance…

Much remains to be understood about how 60YC might become the future of higher education. In my opinion, the biggest barrier we face in this process of reinventing our models for higher education is unlearning. We have to let go of deeply held, emotionally valued identities in service of transformational change to a different, more effective set of behaviors. I hope higher education will increase its focus on the aspirational vision of 60YC as an important step towards providing a pathway to a secure and satisfying future for our students.

Excerpt from the The EvoLLLution online newspaper, 19 October 2018
by Christopher Dede, Ed.D., Wirth Professor in Learning Technologies, Harvard University [18]

Instead, they should be leading the way to optimize experiences and systems of learning (which may or may not involve technology), and helping organizations meet their missions through the growth and evolution of their training and education programs. This will require learning engineers to work both together with other experts and on their own to navigate client expectations, integrate emerging capabilities, choreograph complex interactions, and help learners achieve more efficient and effective results.

Conclusions and Recommendations

As the learning ecosystem becomes more complex, those who teach others, whether they are facilitators, faculty members, or other professionals may well find it difficult to keep up with the changes. Instructional designers and learning engineers are specialists in education and training; they can help teachers, trainers, and organizations transform teaching and learning environments for the modern age, and they can also help fellow learning professionals expand their own knowledge and skills in the use of best practices for education and training.

Instructional designers and learning engineers have complementary skills and knowledge. They both have a thorough grounding in the learning sciences and an ability to identify appropriate instructional interventions, but learning engineers will provide more data-driven solutions and focus more on advanced technologies and enterprise-wide elements.

As these positions evolve, we need to ensure instructional designers and learning engineers have defined responsibilities and roles, so that both they and their organizations know whom to approach for different needs, understand how they work together, and can uniquely value each skill set. Overall, we need to recognize the benefits that both instructional designers and learning engineers bring and, thus, ensure they continue to play an active, valued role in project teams, organizations, and the larger learning community.

CHAPTER 17

GOVERNANCE FOR LEARNING ECOSYSTEMS

Thomas Giattino and Matthew Stafford, Ph.D.

The transition from independent systems to a learner-centered ecosystem is attractive to learning professionals who have previously undergone a similar evolutionary process in their field. Readers may recall the first forays into online learning, which largely emerged within individual programs, departments, or colleges. As enrollment and interest grew, other organizations went online as well, resulting in duplication and increased costs. In most instances, an overarching entity—an agency, industry, school district, university, or university system—stepped in to harmonize the e-learning systems, standardize their technology and approaches, and ensure e-learning results were captured and reported similarly. Today, as the learning ecosystem reaches maturity, the question emerges: who will run it and how?

In dealing with competing and constantly changing demands, limited resources, a vast array of products and capabilities, and a need for integration across their systems, learning professionals recognized the need for an overarching governance structure.

Heraclitus of Ephesus noted, "Life is flux; the only thing that is constant is change." Learning professionals will certainly agree; their field has changed—and continues to change so rapidly that it's difficult to keep abreast of developments. The proliferation of content, the myriad delivery modalities, and even the collective understanding of how the human mind actually learns have

driven these professionals into near-constant reconsiderations of their field and all it encompasses. Learning professionals have reacted to this flood of capabilities by stitching together patchwork systems of systems. As teachers approach them with new requirements, usually coupled with a request for a new technological capability, learning professionals have expanded their patchworks accordingly. The result is a workable set of individual tools, but only just. Often, learners and teachers have to switch between capabilities—a tool for audio/video, another tool for asynchronous chat, still another for synchronous collaboration. It is a "time of plenty," but it is also plenty confusing!

Learning professionals are starting to describe these product-and-service composites as "ecosystems," with the term "ecosystem" adopted from biology. Scientists describe ecosystems as groups of living organisms interacting with one another and with their environment, with a high level of interdependence. Some ecosystems, such as an ecological biome, are ungoverned, but others have some centralized mechanisms. A good example of this scientific understanding is the human body. The various organs each perform specific functions, but they work together, within an environment that provides oxygen and nutrients, to ensure the overarching system (the body) functions successfully. It's a complex system of systems that's also managed centrally, as all of these functions are governed by the human brain.

Without centralized governance, the various components of an ecosystem cannot maximize effectiveness and efficiency.

For our learning ecosystem to function optimally, it needs centralized coordination, but where should it come from? An initial, obvious answer is to look towards technology vendors. For instance, Apple was an early leader in the system-of-systems technology movement. Apple realized it could increase its market share by making all of its devices work with one another and by simultaneously allowing users to personalize their networks, build content,

> Most of our challenges have been cultural and political, not technical nor operational. If people can see the big picture, and they can see where they are and why it makes sense, it can be very beneficial. If I can get them to see it, then they can understand it, and more importantly, they can carry the message to the next office because it makes sense.
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> **Reese Madsen**
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and control their cross-platform experiences. Microsoft and Google followed suit. In each case, the connection between customers, their hardware, online capabilities, and content increased the effectiveness of each component and, in turn, its value to customers.

Looking to large-scale technology or media companies to orchestrate the interoperable systems, implementation and operation processes, ethics and norms, and organizational policies for a learning ecosystem, however, is a risky prospect. The learning ecosystem concept necessarily involves many diverse components, likely derived from different vendors, across organizational boundaries, and for different phases and aspects of learning. Seeking centralized oversight from a single corporation risks "vendor lock" or confinement to potentially expensive and proprietary solutions. Further, many key aspects of governance extend beyond technology, media, data, or delivery. Each organization will want to answer these sorts of questions for itself, away from the commercial interests of even the best-intentioned industry organizations. For instance, how an organization chooses to use learners' data, how tightly coupled talent development systems are with human resources functions, and how best to negotiate between stakeholders' competing requirements are all key governance considerations.

We're such a small state that we can't build our own systems. This means we need to be the best "masher-uppers." We've worked with other new England states, but now we're focused more broadly. It's not so much urban versus rural, it's that we're an outlier, a progressive state that's always focused on the individual learner. We're in a slightly different place than other states because we're not a top-down, centralized education system. Rather, we put a lot of emphasis on local control.

Daniel French
Secretary of Education, Vermont Agency of Education

For the most part, too, education and training vendors have been less concerned about governance and more concerned about sales. Governance is a customer concern. So then, the question for customers—for those organizations who design and deliver learning—is: How do we create a governance structure that both centralizes general oversight of the ecosystem while simultaneously maintaining necessary flexibility that allows for content ownership by communities, data ownership by users, and tool creation by developers?

E PLURIBUS UNUM
(OUT OF MANY, ONE)

A look back through American history provides an instructive example of how one might develop a governing structure for an ecosystem. Like the independent systems of the first educational forays into online learning, early American settlements existed in relative isolation from one another. The settlements were responsive to their inhabitants' needs but looking holistically, there was a great deal of overlap and duplication in governmental functions. Each settlement handled its security, infrastructure, communications, and transportation needs often without even considering other settlements. As these settlements grew, interdependencies developed to create colonies. Each colony had its individual identity, its own governance structure and, as with settlements, only limited concern for the wants and needs of neighboring colonies. This changed, however, with the arrival of a common threat.

The move toward independence from England, which precipitated the arrival of what was then the world's most capable military force, drove a loose alliance among colonies. At first, the colonies attempted to keep their independent identities, with primarily decentralized control; however, this first governance structure, the *1777 Articles of Confederation*, proved a failure. The *Articles* failed to create a sufficiently strong, centralized government capable of guiding the fledgling nation. This resulted in infighting and made the central government unable to overcome challenges or capitalize on opportunities collectively.

As the weaknesses of this confederated approach became obvious, representatives from across the colonies—the men who became the Framers of the Constitution—gathered to reconsider their centralized form of governance. Some argued emphatically for simply modifying the *Articles*, retaining the balance of power at the colony level. Others took an enterprise approach, ar-

guing that only a strong, centralized government would be able to quell the bickering that had made the *Articles*-based government so ineffective.

In 1788, the Framers' U.S. Constitution was ratified, implementing a unique "federalized approach"—a state within a state in which the former colonies (now "states") were provided the authority for tactical issues, while the centralized government retained supreme power and oversight to deal with those issues affecting the enterprise (the entire nation). Such a "federalized approach" to governance is an ideal structure for learning ecosystems!

The evolution from a loose affiliation of learning-focused entities, each with its own needs, systems, and rule sets, to an overarching centralized governance solution parallels the Air Force's experience in designing and deploying its "Learning Services Ecosystem." From the authors' interactions with other agencies, the evolutionary track is remarkably similar for a wide variety of organizations, whether from the industry, academic, or government sectors. In each instance, success was predicated on the organization's understanding of, and commitment to, an enterprise solution coupled with the ability to receive, evaluate, and act on the varying needs of all organizational constituencies within the ecosystem. In other words, where governance has proven most successful, there's been an intentional balance between individual constituents' needs and the centralized needs of the community.

Since humankind first saw the need to join together to satisfy common needs, there has been some form of governance. Learning ecosystem governance is no different. An effective governance structure is born out of a small group of professionals who decide to combine their individual needs, capabilities, and resources to provide better support for, and service to, their organizational constituencies. These professionals come together to discover the breadth of the organization's stakeholders and the key issues to be addressed. They then work across the organization to select representatives—the framers—who

discuss the issues, create an ecosystem charter, and manage its governance over time. It's a labor-intensive and emotional process, but when successful, it's an extraordinarily fulfilling undertaking.

IMPLEMENTATION

The process through which ecosystem administrators can design and implement a governance structure, necessarily includes the following steps:

Step 1: Identify Stakeholders and Select Framers

The first step in establishing governance necessarily involves identifying the breadth of inclusion: Which entities (colonies) will be included and which will be left to fend for themselves? Next, there has to be an opportunity for the entities to come together to share their wants, needs, expectations, and resources. These stakeholders will become the initial architects of the ecosystem governance structure. To make this opportunity successful, organizers must ensure the appropriate representatives are selected to participate. These representatives will become the "framers" of the new ecosystem charter. Organizers can consult with stakeholders for nominations but may also ask to have certain personnel appointed for their special skills or knowledge.

Because of the technological focus of ecosystems, organizations are likely to send representatives from their most technologically advanced programs: technology experts who understand systems, data, and the capabilities available in the marketplace. This is expected and desired; however, representatives from all stakeholder groups need to be included as well. Collectively, the framers will need to understand the entire organization's needs, products, processes, and capabilities. Without a holistic understanding of the organization, the framers are likely to ignore key constituencies or issues.

The framers should also include members who can think locally, addressing individual requirements and concerns, while also thinking globally to understand an enterprise perspective. It's not always possible to find people who can do both; so, organizers should try to find a balance among the selected members to ensure all the constituencies are heard. The result shouldn't be a patchwork of individual interests, rather the collective perspectives should inform an overarching strategy for addressing the broadest array of requirements and desires.

Step 2: Select Issues

Once the constituencies are determined and framers selected, organizers will need to consider the breadth of topics to discuss. The selected framers will undoubtedly expand the discussion when they meet, but it's necessary to have "an entering argument"—a list of key questions to answer. These will vary with each organization's unique situation; however, the following brief list might prove helpful in building a governance conference, as they are somewhat common to most organizations:

MEMBERS

1. Who determines who "joins" the ecosystem? One centralized administrative function involves determining who may "join" both in terms of people and organizations who want to belong, and also in terms of systems and capabilities that constituencies might want to integrate into the ecosystem. The governance structure must provide avenues for entry and, simultaneously, ensure new people and new capabilities aren't injurious to others within the enterprise.

2. How will constituencies be replaced? Representation is foundational to the success of a governance structure, as it ensures constituencies have a voice in the design, development, and direction of the ecosystem across its life. There's a risk in representation, however. Constituencies need to be heard,

Members
Who determines who "joins" the ecosystem?
How will constituencies be represented?
How will governance structure be organized?

Policy
Who is responsible for establishing centralized policy?
Who will enforce policy?
How can enterprise-level functions be supported?

Resources
Who will provide the resources and how?
Who will provide support and how?

Key questions to answer...

Processes
How can the ecosystem address change?
How can the ecosystem remain relevant and responsive?
How does the ecosystem interact with partner/other organizations?
How will users experiment and adapt?

but the governance structure must ensure no single constituency takes control of the ecosystem to the detriment of others. In addition to rules for expected behavior, mechanisms are needed to censure misbehaving representatives or shed inactive ones.

3. How will the governance structure be organized? There are multiple approaches; however, an approach needs to be selected, coordinated, approved, and promulgated so all constituents understand where their representation lies, where decision-making authority lies, and where they can go to request reconsideration of their proposals should they be denied. The model adopted by the Framers of the U.S. Constitution (the federalized approach) is worthy of consideration: The centralized ("national") government oversees enterprise-level concerns while subordinate organizations ("states") have the capability to make certain changes to keep their operations moving.

POLICY

1. Who's responsible for establishing centralized policy? Like the federalized approach to U.S. governance, some functions and decisions will affect all constituents, while others are best handled locally. It's necessary to determine the functions that affect multiple constituencies, as well as the constituencies' needs and processes for managing these centralized functions. How will aggregate requirements be identified, needs agreed upon, decisions made, and results promulgated across the ecosystem?

2. How will the ecosystem address change? Change is difficult. Framers will need to consider a variety of potential scenarios to devise a system responsive to change. The following scenarios present examples framers might consider:

U.S. AIR FORCE LEARNING ECOSYSTEM GOVERNANCE

The U.S. Air Force is deploying their **Air Force Learning Services Ecosystem**. Air Education and Training Command built the ecosystem and also established its charter, a managing body that oversees its operation, and its policy and support structures.

The ecosystem's governance structures were adopting from the model prescribed in the *IT Infrastructure Library*, the British Government's guide to IT service management. It's a hierarchical model, much in line with the approach prescribed in the U.S. Constitution. For the U.S. Air Force, at the enterprise level, there's Force Development Governance, overseeing how the Service will develop Airmen, how many will be developed, and in which areas. Below that, there's an operational level of execution—Air Education and Training Command—overseeing the specific programs supporting Force Development and IT/Educational Technology.

Air Education and Training Command manages ecosystem operations with a level of decentralized execution, so stakeholders can address their own concerns, but where users' concerns have the potential to affect the entire ecosystem, they're elevated for an enterprise-level solution.

- A new training program is created per a senior leader's directive. Its administrators wish to claim to high levels of synchronous bandwidth. Ecosystem administrators need to know how this will this be funded.
- Multiple games and simulations run within local systems. Ecosystem administrators will have to determine which will migrate to the ecosystem and what opportunities might exist for sharing technological advances inherent in the best of these with other ecosystem users.
- Senior leaders have opted to increase the workforce. Ecosystem administrators will have to determine how the enterprise will support this increase in throughput. If external education/training is required, they will also have to ascertain how the ecosystem will track learning occurring outside of the organization.

3. Who will enforce policy? This is an important consideration, as constituencies will often bring special talent to bear to change or incorporate new capabilities, software, or hardware into the ecosystem. How will unauthorized variations be detected and how will they be handled?

RESOURCES

1. Who will provide support and how? Support is a complex topic and one often overlooked in the rush to bring aboard new capabilities. Systems tend to come with "a maintenance tail" to keep them functioning effectively and current to industry and security standards. More importantly, users—be they teachers, learners, data analysts, or records keepers—need support too. The governance framers, in their desire to balance enterprise-level and individual constituency-level concerns, may opt for the federalized approach, where some level of support is provided locally and other support nodes are centralized for the entire ecosystem. Support is often a major hurdle for framers as new ecosystems come on line: Users will want to retain their existing support capabilities while ecosystem administrators tend to favor centralized approaches. This is a critical resource consideration.

2. Who will provide resources and how? This question should drive framers to discuss the sources, types, and quantities of resources required, and who can provide them. It's a broad category, encompassing money, manpower, machines, infrastructure (facilities, electricity, internet capability, etc.), and much more. Some resource considerations follow:

- **Funding** – Centralized funding is attractive for constituencies but, without their investments, they may find it easier to strike out on their own when decisions don't go their way. Framers shouldn't underestimate the power of constituencies "having skin in the game!" For government entities (and some non-government organizations as well), we often find financial resourcing extraordinarily complex, as funds are split across organizations and labeled for very specific expenditures. "Pooling resources" becomes surprisingly difficult, which creates a risk of promoting individual actions and encouraging redundancies. Framers should ensure their resourcing strategy doesn't create "insurgencies" within their organization.
- **Manpower** – The pooling of manpower is often recommended as an approach to enhance efficiency; however, it's often predicated on a notion that dispersed manpower possesses some level of excess capacity that will be employed most effectively if amassed. That's not always the case. If five people, working in five organizations, are overwhelmed with their existing workloads, having them bring their workloads to a common location will simply increase the difficulty they experience serving their former constituents–making them even more overwhelmed. So, while there's often value in centralizing some functions, care must be taken to be realistic in the level of effort required and to find the best balance between local and centralized labor resources.
- **System integration** – For good reasons, constituencies will often argue to retain their systems. Training and conversion costs, and the trauma of switching systems, are very real concerns. Yet the governance struc-

ture will have to find efficiencies and ensure that systems work together. Recognizing potential duplications and overlaps, and dealing with these fairly, is an important part of technological governance. Those constituencies forced to adapt must receive sufficient assistance to ensure their operations are not adversely affected.

PROCESSES

1. How will users experiment and adapt? The educational technology market is changing constantly. Users will want to explore new capabilities to meet their organizational needs. Restraining creativity will frustrate users and drive them out of a centralized-governance approach. The best way to counter this is to provide space for experimentation—an "innovation sandbox." This approach supports the insatiable appetite of some users for tinkering; however, it also drives these users to follow system protocols that govern the entire ecosystem. This approach benefits all: The ecosystem is not corrupted by experimentation, and those experiments that prove worthy of pursuing have already demonstrated an ability to function within the ecosystem successfully. An additional benefit is the way this approach aids in "policing." The innovators who leverage the sandbox are much less likely to try to sneak capabilities

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OVERALL, TOP DOWN CONTROL OF SCHOOLS IS PROBLEMATIC. We need more of a resource model that focuses on the question, "How can the top help you do your job?" to encourage more autonomy, diversification, and innovation. When you have a really bloated bureaucracy, it doesn't help people.

Benjamin Nye, Ph.D.

Director of Learning, Institute for Creative Technologies, USC

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onto the ecosystem (with potentially dire consequences for the enterprise) if they have an approved place and method for experimentation as well as a way to advance their successful innovations to the central governance structure for adoption into the ecosystem.

2. How can enterprise-level functions be supported? There are organizational-level decisions that must be addressed within the ecosystem, such as the workforce end-strength, qualifications the workforce must meet (learning needs), and the transcripting or certification of learning. All of these questions, and many more, must be considered by the framers establishing ecosystem governance. For the Air Force, negotiating the enterprise-level functions required participation from several overarching working groups, including the Service's Force Development Council, which addresses strategic-level considerations affecting training, education, and experiential learning; an Air Force Learning Council, which determines content requirements for specific programs; and an Air Force Educational Requirements Board, which determines advanced academic-degree and professional military education requirements for Airmen. Each of these strategic-level bodies has data requirements, and each produces decisions that drive ecosystem functions.

3. How does the ecosystem interact with external or partner organizational systems? If the learning ecosystem is set up to provide certificates, badges, or some other credential, are talent-management systems capable of leveraging those credentials for decision-making? Will supervisors have the means to verify employees are properly trained to perform specific tasks? The integration of the learning ecosystem into the overarching organizational IT structure is foundational to its value to the organization. This is complicated, requiring a strategic mindset to establish and maintain integration. Two examples will help explain an administrator's concerns:

- A partnering organization wants a reciprocal arrangement through which their employees can learn within your ecosystem and receive credit electronically, delivered to their personnel records system. Your

leaders want the same for employees who train in their programs. Ecosystem administrators will have to craft these reciprocal agreements and develop the data-transfer capabilities to make these arrangements successful.

- A local community college would like to partner with the organizational training unit to offer associate degrees. The college wants access to the employees' training records as well as the ability to report courseware completions back to the ecosystem. Senior leadership agrees; they want this too.

4. How can the ecosystem remain relevant and responsive? There must be mechanisms in place to ensure stakeholders have awareness of what's transpiring within the ecosystem and have a voice in its evolution. There also has to be some level of senior-leader oversight to adjudicate disagreements that arise between stakeholders and ecosystem administrators. Lastly, like the U.S. Constitution, there must be a mechanism for updating the governance structures and policies. How will the organization drive change in the ecosystem to ensure it continues to meet the needs of the future?

Step 3: Build a Charter

Once all issues have been debated and preliminary decisions made, the framers should produce a charter. This, in effect, is the ecosystem's constitution, describing the manner in which it will function and prescribing the processes by which it will remain responsive to organizational and user needs. A published charter ensures common understanding of authorities, decision-making, and resource-allocation processes, and it outlines steps stakeholders can take to resolve disagreements or seek change. The charter should be coordinated through stakeholders' organizations and concerns adjudicated by the framers before final, senior-level approval and implementation. Once approved, ecosystem administrators must adhere to the charter precisely. Doing so ensures

transparency in ecosystem administration but also serves to reduce the number of complaints or offer a credible defense should complaints surface.

Returning to the Heraclitus quote that began this chapter, "Life is flux; the only thing that is constant is change." Ecosystem administrators will face change. Charters are created for specific needs at specific moments in time. Those needs can change. The U.S. Constitution, for instance, was ratified in 1788. In the course of its existence, 33 amendments have been proposed by Congress and sent to the states for ratification. Of these, only 27 have been ratified and have become part of the Constitution. Arguably, each of these proposed amendments represented a disagreement between contemporary Americans and the Framers; disagreements that must be addressed and resolved. Through the ratification process, the nation keeps its governance aligned with the nation's evolving needs. Ecosystem charters need to be similarly responsive. Change should be possible, but the change process should be sufficiently difficult, so the charter isn't in constant flux. Should that happen, the charter will lose its power and meaning. All stakeholders should have a voice in changes to the charter, so they can weigh the advantages and disadvantage and respond appropriately.

Step 4: Coordinate (Ratify!) the Charter

There is a tendency, within modern organizations, to employ a hierarchical "coordination process" for the approval of organizational positions or initiatives. This seems logical; however, in returning to the example of the ratification of the U.S. Constitution, one can discover even more wisdom in the Framers' approach: Although the Constitution established a representative form of government, where elected and appointed officials would bring the needs of their people forward for debate, it's interesting to note this isn't the system the Framers established for ratification of their governance structure, their Constitution. Instead of handing this task to legislative bodies— the established hierarchy of governance—the Framers authorized "conventions." They

understood the existing colonies' governance structures might not be inclusive enough, so they authorized this approach. Conventions were held across the nation. Most had lax participation requirements, much more permissive than the requirements for a governmental position. As a result, a vast array of constituencies could step forward, air concerns, and identify strengths and weaknesses in the proposed constitutional-governance structure.

> We need a common space where key actors in postsecondary learning can coordinate without hampering innovation. It's an important piece of bringing the systems together. We need touchpoints without over-programming.
>
> **Amber Garrison Duncan, Ph.D.**
> Strategy Director, Lumina Foundation

Ecosystem administrators should be equally inclusive in establishing their "governance conventions," to maximize inclusion. They should provide the charter to the various stakeholder groups to let them discuss it and provide input. Certainly technology experts must be consulted—but so must personnelists, organizational planners, and, of course, trainers and educators. They will guide organizers in building an ecosystem that delivers learning effectively. Since the ecosystem will produce data, it's also important to include those people who will have to access and employ ecosystem data. Consider providing the charter to the registrar or human-capital record-keeping departments. Lastly, don't forget the learners! To maximize effectiveness, the learning ecosystem will have to be designed, developed, and deployed with learners in mind. How will the system meet learners' wants and needs if they're excluded from the governance discussion? Consider "conventions" carefully; those excluded from consideration are likely to become the most resistant to the resulting governance structure.

Step 5: Build Responsiveness into Administration

Much in the same way that organizers cast a wide net in establishing their conventions, ecosystem administrators should ensure all stakeholder communities remain aware of and involved in the evolution of the system. This requires managers to identify and continually refine the requirements of the supported population. “Responsiveness” is the watchword, requiring managers receive and respond to needs quickly and accurately.

In addition to responding, ecosystem administrators must be proactive in providing feedback to stakeholders on system operations. Metrics, for instance addressing support, system functionality and availability, and costs, are invaluable for ensuring stakeholders are attuned to the enterprise-level requirements of the ecosystem. These must be provided to stakeholders regularly and can also guide senior leaders’ resourcing decisions for ecosystem investments.

Although the governance structure has already been addressed, with the need for each stakeholder to have a voice in system administration, ecosystem administrators must ensure there’s transparency in this process. “Frequently

School districts are a traditional, sole-service delivery model, and districts have exclusive rights over the learning needs of the students assigned based on residence. They have to be all things, to all kids, all of the time. This is impossible, and it’s arbitrary because it’s based on just where you live. If a kid wants something but the school doesn’t have it, we assume the kid is wrong but the system is right. For example, if a kid in a rural community loves art but the district doesn’t offer much art, we ask the kid to put the passion on hold and instead get excited about history or some other offering the district is good at. We say that the district is right and the student is wrong—in a deep profound way. But the kid and family are right and the system needs to adjust and adapt to provide those pathway options. Of course, districts can’t do it alone; they have to form partnerships.

Ken Wagner, Ph.D.

Education Commissioner, Rhode Island Department of Education

asked questions," chat rooms for stakeholder feedback, meeting minutes for governance meetings, and regular, open communications between administrators and stakeholders are critical to building trust across the organization. Administrators should also alert users to current and upcoming problems, maintenance schedules, and actions taken to resolve problems. Too much information is better than too little in building trust. Resources are limited, and administrators invariably have to deny stakeholders' requests. Trust and transparency aid considerably in how a negative response is received and perceived.

Administrators must also engage stakeholders in bringing aboard new components. Cooperative efforts that maximize participation can expand interest in and support for new capabilities. In addition, administrators may find stakeholders who can benefit from such initiatives willing to share resources for their implementation.

Step 6: Address Grievances

Although cooperation is the aim, there will be disagreements. There must be an organizational "court of appeals" for those situations where administrators and stakeholders disagree. There must also be a level of strategic oversight to ensure the ecosystem and all its stakeholders are moving together to satisfy organizational needs. Most organizations have some level of "corporate structure" that facilitates strategy-making, execution, and decision-making. Ecosystem administrators must ensure their operations are included within that corporate structure. To ensure their senior leaders comprehend the value of ecosystem operations and the challenges faced, administrators should report regularly to senior leaders. Within the Air Force, for example, ecosystem administrators periodically send written reports to Major Command commanders and Air Force senior leaders. In addition, there's an oral report—the *State of the Command*—that specifically addresses the ecosystem and is delivered by the Force Development Commander to the assembled body of Air Force senior leaders at an annual conference.

> We need a new approach that enables our people to innovate effectively across the DoD training and education domain. There's good strategic guidance from our government leadership, but it's not carried forward in a meaningful way because it's negated by excessive and often misinterpreted policies. The problem is further compounded by competing interests, stovepipes, and lack of resources.
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> A new approach should actively pursue and remove irrelevant administration, process, and governance that kill modernization and rapid-development initiatives. A new approach should get people from out behind their desks and away from "business by email." Finally, a new approach should encourage face-to-face exchange of ideas, better cross-organization coordination, and dedicated investment in discovery activities outside of the traditional R&D mechanisms. Only by doing these things will we truly achieve the transformational goals expected of us working in the training and education space.
>
> **Dennis Mills**
> Program Analyst, Naval Education and Training Command, U.S. Navy

SUMMARY

This chapter described the evolution large organizations must make as they move from functionally isolated information-technology schemes toward enterprise solutions. The example of the American colonies' transition from relatively independent polities, to loosely affiliated states, and later to interdependent states governed by a constitutionally ordained centralized government, provided a foundational metaphor to help readers orient to this evolutionary process. In our case, today's functional, formerly independent learning institutions will need to come together. Although, they'll still require some level of autonomy to address local events and requirements, events with

a broader impact must be handled at the enterprise level, across the learning ecosystem, to capitalize on opportunities, reduce costs, and avoid unintended consequences that can occur within this complex system of systems.

Organizations can take steps to ensure their governance structures remain attuned to stakeholders' needs, are stable to ensure dependability, and are simultaneously flexible to support growth and innovation. Establishing these internal governance structures is a critical first step in deploying an effective learning ecosystem supports, and remain concurrent with, evolving learning needs and opportunities.

As with nations, initial governance starts at home, by establishing processes, policies, rules, and norms for managing an ecosystem within a given organization. Over time, different organizations will encounter more opportunities for interdependency, and new external governance structures, like the United Nations or World Trade Organization in our metaphor, will be needed. As we ponder the enormity of governance required for lifelong learning systems, however, it's useful to be reminded of Gall's law, written by systems theory critic John Gall:

> A complex system that works is invariably found to have evolved from a simple system that worked. A complex system designed from scratch never works and cannot be patched up to make it work. You have to start over with a working simple system.[1]

The most advanced learning ecosystem efforts will ensure all system components work together, that learning is captured and reported across organizational and temporal boundaries, and that the entire construct is learner-focused, giving users control over their learning and, to the extent possible, their learning environment. Yet, for such an overarching system to be successful, it must start locally, with well-developed processes and mature governance methods within individual enterprises. Over time, then, we can extend those approaches out, building the complex, lifelong learning ecosystem across our societies—albeit, one step at a time.

> Everything people want is obtainable, but there's a great deal of myopic thinking, especially within the government. We hear too often, "We've never done it that way, so why should we change now?" The focus is too often less about the mission and more about the change. Having a good change agent is key. We need the executive branch pushing from the back and Congress pulling from the front. It needs to be a comprehensive system to be effective.

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CHAPTER 18

CULTURE CHANGE

Scott Erb and Rizwan Shah

Our current learning systems were developed in response to the industrial revolution and the accompanying shift from an agricultural civilization to an urban, manufacturing society. The focus of much of education and training was to produce people ready to enter the workforce with predictable, well-known, replicable skills that matched the needs of the industrial economy. In order to produce these workers, the system required teachers who also had predictable, well-known, replicable skills in teaching. Thus, a system of "normal schools" was built to train teachers.[1] But as we shift to an information economy, a new set of skills not easily taught within the existing education and training framework will be required, which will drive a shift in the way we imagine, approach, and develop learning experiences.

Rethinking learning from the industrial model to the information model will necessarily be disruptive to existing organizations. The adoption of new learning science methods and technologies will require change to their cultures, shifting away from incremental compliance cultures with established delivery and assessment methods to more fluid multiplatform and multimodal methods, coupled with pervasive data capture and advanced analytics. Organizations able to successfully navigate this cultural change will thrive; those unable to do so will be left behind.

This chapter discusses some considerations for the change in culture that will be needed to modernize learning, remove barriers, and restructure incentives to inspire the organizational shifts needed in order to achieve the future learning ecosystem.

> The **culture shift**—that's probably the most difficult thing to navigate.
>
> **Kurt VanLehn, Ph.D.**
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FEAR OF CHANGE

Undertaking significant organizational changes can create feelings of uncertainty, anxiety, and being threatened.[2] When the area of change is something as fundamental as learning, such fears can multiply.[3] If not adequately addressed, these feelings can manifest as either passive or active opposition, resulting in immediate failures and resistance to future attempts.[4]

There are various human factors that make change difficult,[5] some of which are particularly relevant for the future learning ecosystem. For instance, consider the fear of automation. The potential for AI to replace workers in the economy, including teachers, doctors, and lawyers, has been widely publicized in the popular press over the last few years.[6] This has had the effect of amplifying the natural fear of one's skills becoming obsolete in a changing economy.

Another, related example, involves the fear of losing of control. The imposition of change may make individuals feel their self-determination is being undermined, particularly when that change involves increased automation, complexity, and difficult-to-understand data analytics. Individuals might feel uncertain about their roles, the direction of the organization, or their abilities to contribute and maintain relevance.[7] Team members who were instrumental in creating the current way of doing business may worry about the perception

that the need for change means their way had failed. Similarly, those who help administer the current system (such as the present-day teachers, trainers, and instructional designers) may wonder whether they'll be able to translate their current skills into the new environment—will they still be competent and be viewed as competent by others?

> *"Nothing so undermines organizational change as the failure to think through the losses people face." – William Bridges*

Add to these underlying insecurities the fears of increased scrutiny. Data analytics, increasingly important in all aspects of learning and absolutely critical to measuring the effectiveness of changes in a learning environment, may cause concerns that instructors or program managers will be held adversely accountable if the data don't demonstrate high levels of perfection. Learners may feel exposed and uncomfortable, as well, as the data we can collect and analyze gets richer and more actively informs a growing range of actions—not just within a given learning episode but potentially affecting jobs, careers, and lives.

Another reason some resist change is because it looks like additional work. In general, production must often continue in the existing system while new systems are established;[8] this is certainly the case for the future learning ecosystem. Add to that the new processes and requirements of the future system, the looming prospect of ongoing lifelong learning, and the complexity of it all. It seems like a daunting task.

Combined, these form a landscape that leaders of organizations seeking to innovate must understand and successfully navigate. Discomfort with change may manifest in different ways as an organization attempts to implement it. Within sufficiently established bureaucratic organizations, resistance can be accomplished by citing page and paragraph of existing policy, or by constructing unnecessarily onerous approval processes. People with a long his-

tory within an organization, and who may have seen several generations of leadership, may become passive resistors—intent on waiting out the latest fad while continuing to execute the status-quo processes they're responsible for.

However, for organizations to remain viable they must embrace—appropriate—change. If not, organizations that were once industry leaders can fall behind, or worse, close their doors altogether. In which case, those who resisted the change, and the leaders who failed to overcome that resistance, will have helped bring about the downfall that they believed they were preventing. A tough situation, but there are proven techniques to facilitate culture change and maximize the probability that the change leads to better outcomes.

CHANGE MODELS

There are several change management models that are useful across a variety of settings, and which can inform options for creating acceptance to advance learning (see adjacent figure).[9] The models vary in complexity. Some have only a few steps, but these fail to target all the necessary areas; others have more detail but risk draining resources and time. As such, no pre-packaged model is sufficient. Rather, a composite of these models, combined with lessons learned from working within government, military, and current education structures, must be utilized.

General Principles for Encouraging Change

CREATE AND COMMUNICATE THE UNIFYING VISION

To begin, each organization requires a unifying vision of why it exists and why it's changing. Organizational consultant and motivational speaker, Simon Sinek, has written extensively on ways to develop this vision; he emphasizes that the first step is understanding the organization's guiding purpose, and

8 CHANGE MODELS

KÜBLER-ROSS'S MODEL

"5 Stages of Grief"

1. Denial
2. Anger
3. Bargaining
4. Depression
5. Acceptance

ADKAR

Awareness of the need

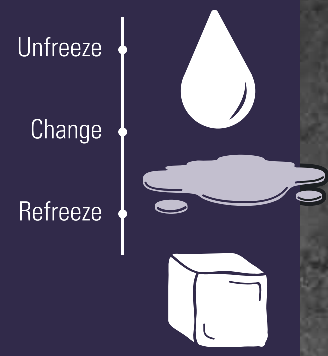
Desire to support it

Knowledge of how

Ability to do it

Reinforcement to make the change stick

LEWIN'S MODEL

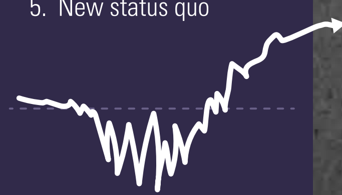


KOTTER'S THEORY

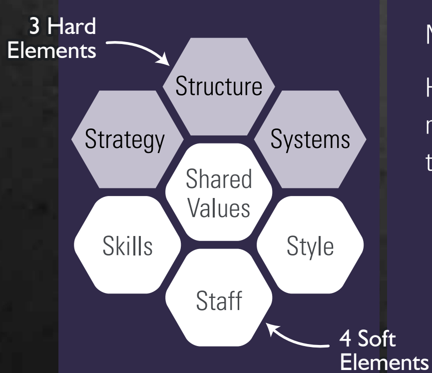
1. Increase urgency
2. Build guiding team
3. Develop the vision
4. Communicate for buy-in
5. Empower action
6. Create short term wins
7. Don't let up
8. Make change stick

SATIR'S MODEL

1. Late status quo
2. Resistance
3. Chaos
4. Integration
5. New status quo



MCKINSEY'S 7-S

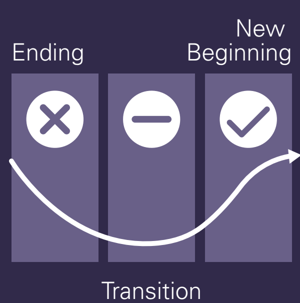


NUDGE THEORY

No set process.

Help people change by nudging rather than using traditional methods.

BRIDGE'S TRANSITION MODEL



that it's most powerful when framed as a statement of belief:[10] *We believe...* The leader must own this statement deeply and personally, yet also develop it collaboratively with her core leadership team. The leadership team must also ensure that every member of the organization understands the vision—the WHY of the organization.

Similarly, it's important to incorporate a vision for the future, one that stimulates unity of effort and inspires individuals to take initiative to move forward. A compelling vision of what the organization looks like in the future helps generate the buy-in and initiative needed to implement change. Sinek stresses the importance of communicating why change is needed and reinforcing the message frequently. Communicating the vision once and expecting it to take hold throughout the organization is a recipe for failure.

Individuals exist within organizations, which exist within communities, which exist within the larger ecosystem. Accordingly, when communicating across this magnitude of diverse constituencies, shaping the narrative for each requires intentional consideration. While managers and administrators may be focused on inputs and efficiency, instructors tend to be more focused on outputs (e.g., how well are the students performing?). Communicating the WHY for change must acknowledge each team member's role and remain grounded in the organization's overarching purpose.

Finally, helping the entire organization (not just the leadership!) contribute to this vision creates ownership, builds a common compelling story, and inspires initiative. It's also likely to generate ideas that leadership didn't consider and to reveal easy early wins to help build momentum. Open-ended questions can help drive creativity here, for instance: What does the new normal look like, feel like, and sound like? How do our students or employees say that they imagine the future? What feedback might instructors give to leadership, if the new system is working? What feedback would indicate that an experiment isn't working? What new problems does success create? Are we ready to recognize and take on the new challenges? What are the characteristics of

a learning organization? How might we change the way we communicate to improve organizational learning?

It's also useful to identify key influencers at this phase in the change management process; they can help carry messaging throughout an organization and across different stakeholder groups. The influencers may not necessarily be the most senior people (those with the formal authority); rather, they should be those with the social leadership to influence the rest of the organization. Once adequate levels of initial awareness and buy-in have been achieved, the organization can begin experimenting with process or technology changes.

ENABLE EFFECTIVE COLLECTIVE ACTION

Innovative organizations rarely fail from lack of vision. Often, ideas are plentiful, while implementation is lackluster. Innovating, especially within large, established, and successful bureaucratic organizations depends not only on having a sound vision but also on the ability to manage the organizational disruption that change entails. However, it's not the leader's responsibility to design and manage the implementation plan; rather, it's critical that the entire organization participate. The leader's job then becomes to do only a few difficult things: (1) inspiring the team to pursue the "why" by doing things that generally move the organization in the right direction, at generally the right speed, (2) ensuring the team has the resources to make progress, frequently by removing resistance, and (3) creating safety for the team by putting the innovation and culture change risk on her own shoulders.

The leader must resist, at all costs, the temptation to answer specific questions in any form of "just tell us what you want us to do." Providing detailed instructions for HOW to achieve the WHY is all but guaranteed to derail the innovation and accompanying culture change efforts. The leader must give ownership to each team member (at the appropriate levels) to decide what to build and HOW to build it. There are a variety of ways for the leader to communicate this transfer of ownership, perhaps the most simple is to ask the

questioner for his intent, followed by asking whether that intent enhances the organization's WHY.

The team should then craft a process for how they will implement the innovation and the change-ideas of the team. While the team should craft the process themselves to ensure that the right domain expertise is incorporated and to provide ownership of the outcomes, some general principles should be followed to address common sources of resistance and their underlying causes.

ANTICIPATE AND HANDLE RESISTANCE

Leadership's approach to implementing change, and ultimately to creating a culture that thrives in rapidly-changing environments, must acknowledge the fears that change can cause, recognize how those fears manifest in the organization, reframe them into aspirations with a strong explanation of "why," create safety for those who implement the change, demonstrate (rather than just state) that failed experiments are just as (if not more) important as those that succeed, ensure incentives are aligned to the new culture, and be persistent.

The roll-out for new processes or technology implementations should take into account the sources and manifestations of resistance to the greatest degree possible. Although attempts at perfection here will undoubtedly result in unacceptable delays, failing to have a deliberate process that accounts for resistance will invariably corrupt the results of experiments. If resistance to a new experience is too high, the data collected will reflect the level of resistance rather than the effectiveness of the new process or technology itself.

Notably, the design of the system itself also matters. Too often, early prototypes are designed for minimum functionality but lack corresponding reliability, usability, and user experience considerations—which distracts from the experiment and can turn stakeholders against the entire change process. For instance, the user interface is important. If the new tool takes more than cursory training to begin using, the experiment is not yet ready for the audience. A new technology tool should be easy to understand, easy to use, and

make the end-users feel like they're more effective with it than without it, all within a few minutes. A good rule might be "as easy to use as an iPad for a 10-year-old." Failure to fully appreciate this will strengthen fears of competence, skill obsolescence, or more work. Human-centered design and user interface programming are complex and time-consuming, but users are so accustomed to technology that's well-designed that failing to do so early on may have severe consequences.

The author of the book, *The Checklist Manifesto*, Atul Gawande, notes that he's never seen the "Big Bang" approach to change succeed.[11] That is, dictating a change from the top of the leadership structure to happen at a specific place and time hasn't been seen to work. Clearly an approach that respects the intent of leadership while also preserving ownership of outcomes and processes, and inspiring innovation at the point of contact between provider and customer (in the old model, between student and teacher), is needed. This approach should be common enough to be replicable, but flexible enough to be rapidly tailored to specific cases, and to grow as an organization's experience grows. Furthermore, it should be maintained deliberately to ensure that lessons learned in the change process are collected, understood, and disseminated. If critics see mistakes repeated, they'll become more effective critics! We suggest creating a guide for introducing new projects within the organization. This guide should be owned by the innovation leader (who may also be the organizational leader or a senior member who reports to the leader), and used and updated by the project managers.

Another unique area of concern involves the use of learning data. Clarify upfront what data will be collected and how it will be used. Understanding learning outcomes and modernizing learning will require handling big data and advanced analytics. In learning environments, it's tempting to focus most of our attention on students. Teachers, staff, and program managers will also want to understand that they and their data are safe.

IMPLEMENT INCENTIVES AND REWARDS FOR EXPERIMENTS

Developing a culture that thrives on change depends on the ability to experiment—to innovate, to rapidly try out new ideas, and to learn from these attempts. That necessarily means change, innovation, and innovative organizations are dependent on failing early and at low cost. Consequently, leaders must not only create the time and resources for experiments, but also publicly reward experimentation—*especially* when it "fails." Business, military, and government leaders are familiar with the value of publicly acknowledging team members for exceptional performance, but the norms against failure often make celebrating falsified hypotheses an unfamiliar event.

Astro Teller, director of Alphabet's moonshot factory, Google [x], has a method for doing so that may serve as a best practice for innovators in the learning domain. Teller explains that giving lip service to the idea of "failing fast" isn't enough. Employees need to be free of the fear of punishment—and in fact truly believe they'll be rewarded—for failing fast, that is, for learning and for rapidly sifting through possible avenues for innovation and change. As Teller recently explained in a podcast: [12]

> When one of our projects that actually has, like, a nontrivial number of people, at least a few people full time on it, ends their project…we bring them up on stage, and we say, "This team is ending their project today; they have done more in ending their project in this quarter than any of you did to further innovation at [x] in the quarter." …then I say, "And we're giving them bonuses…You know what guys? Take a vacation, and when you come back the world's your oyster. You'll find some new project to start or you can pick which project to jump into, depending on which one's going best.…The word *failure*, and trying to get people to fail is a bit of a misnomer.…Failure when it's actually just "you got a negative result for no reason and it's meaningless" is a bad thing. I'm not pro-failure; I'm pro-learning.

Culture change is about persuasion!

IMPLEMENTATION PLAN

Connecting the general theories, methods, and models of change management, we recommend a hybrid approach that capitalizes on the key points of each. Six areas of focus are recommended when starting the culture change process for modernizing learning systems.

Educate

The first step towards preparing an organization to embrace the future learning ecosystem concept involves communication and foundational (re)education. Resetting the WHY of the organization is critical to not having to repeat the culture change process with ever-increasing frequency. The future learning ecosystem idea isn't a defined end-state but, rather, a commitment to ever-evolving, learner-focused support via interoperable technology and other emerging capabilities. Our goal, therefore, is to foster an organizational culture that embraces change as a way of life rather than an organization that has successfully navigated from one static state to another.

There's nearly always a fear of change. The goal is to reduce this fear by increasing education about the change. Extra time needs to be spent helping people understand what they need to achieve and, of course, why. It's not just about garnering their buy-in, it's about reducing their fear. Step one, then, is to ensure everyone is educated on the goals for the future learning ecosystem. For example, explaining the value of interoperability at the technological level and envisioning the new methods learners and teachers will use to operate in a human-computer shared space will be important. However, the next step is to listen: To carefully consider stakeholders' fears and give them an opportunity to work through their concerns, contribute to the larger vision, and become ambassadors to the idea in their own ways.

> You have to **unleash** people and **empower** them using climate and culture.
>
> **Ken Wagner, Ph.D.**
> Education Commissioner
> Rhode Island Department of Education

Support

Everyone needs to know where and how to get support, not just philosophically, but also from a management perspective. Within the U.S. Government, the Office of Personnel Management's USALearning program provides an immediate go-to for the development of this system, and the ADL Initiative offers support for research associated with new aspects of it. Within higher education and K-12, other support systems are being developed; for example, the Lumina Foundation and U.S. Chamber of Commerce are working together to support employers and employees making this transition. Further, other standards organizations and professional societies, such as the IEEE, can also offer guidance and recommendations to government, academic, and industry constituents.

Providing resources is another important aspect of support, whether those involve time, labor, or financial investments. We often see situations where people are given a new mission (e.g., "we expect you to increase employee engagement") but aren't given any ideas, resources, or support to aid the process. If people are expected to make changes, they'll need resources to do so—not only to support the change, itself, but also to facilitate the overhead required by the change process. Commitment to change requires resources,

and more than that, it requires a demonstration of "skin in the game" via the allocation of resources.

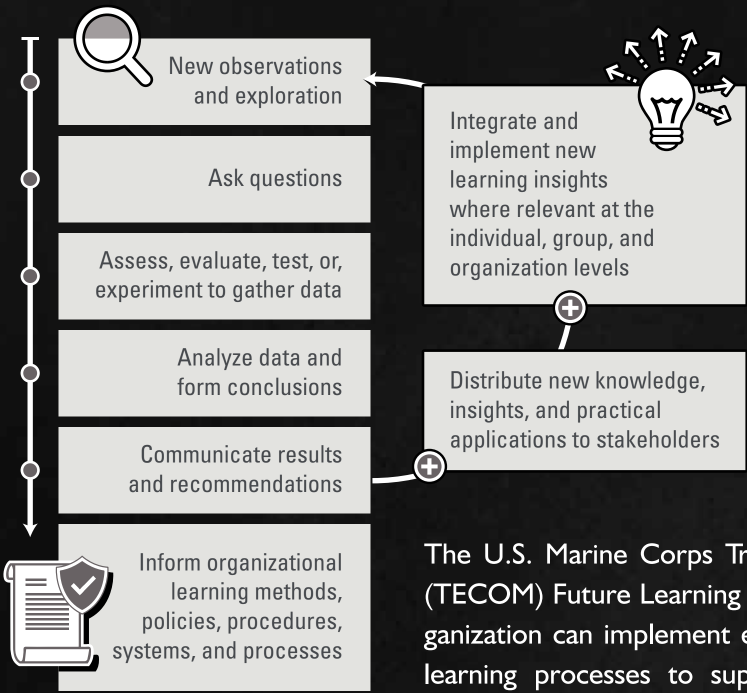
Buy-In

What's the return on investment? That's the question at the highest level, but at personal levels, individuals need motivation and will ask themselves, *what's in it for me?* (or WIIFM, usually pronounced as "wiff-um," a common acronym in military). So, both quantitative, logical messages and more personal, evocative messages need to be crafted. That is, we need to consider both the ROI and WIIFM for teachers, instructors, managers, leaders, senior leaders, and learners, as well as for businesses, schools, universities, and government agencies. They need to understand why these changes need to occur and the pathway through the transition. They need to understand why it will help them personally and how it will be implemented and/or integrated with existing systems.

Making transition feel easy is one of the most important challenges to tackle and among the most important one to get right. This book is meant to serve as an initial step in that process. It's intended to help paint a picture of the "art of the possible" and take the first steps towards clarifying why these changes will improve the system; however, the specific buy-in rationale will be unique to each organization and stakeholder group.

Multi-Messaging

It's one thing to make changes within a small system or even within a department where like-minded or similarly oriented individuals reside. However, once change is nationwide and includes systems of systems as well as multiple communities, it requires multiple but complementary messages to be cultivated and disseminated. In this case, it's necessary to achieve two primary



★ *Example*

ORGANIZATIONAL INNOVATION USE-CASE

From Kendy Vierling, Ph.D., Director, Future Learning Group, USMC TECOM

The U.S. Marine Corps Training and Education Command (TECOM) Future Learning Group demonstrates how an organization can implement evidence-informed organizational learning processes to support innovation. Established in 2017, the TECOM Future Learning Group is a special staff unit that advises the Commanding General of TECOM. Its mission is to seek and assess innovative methods and technologies to improve Marine Corps training and education. The figure above shows their process.

Beginning with "new observations and exploration," the group contributes to organizational learning by **identifying** current and future Marine Corps learning needs, competencies, gaps, and goals—and how they relate to the individual, group, training and education units, and the overall Marine Corps. Next, the group scans the horizon for emerging science and technology, such as augmented and virtual reality–based training simulations, adaptive mobile learning applications, and new methodologies for enhancing instructor development. They **ask questions** to explore the prototypes, **test** new methods and technologies, **gather data** and **analyze** it to form conclusions, and ultimately **provide recommendations** to TECOM leadership. These results and recommendations go on to inform organizational learning methods, policies, procedures, systems, and processes.

The TECOM Future Learning Group also shares the knowledge and practical applications they uncover with stakeholders both within and (as appropriate) beyond their Command. Findings are also integrated into current and future Marine Corps programs at the individual, group, and organization levels, and the results feed-back into their organizational learning process, driving the ongoing improvement cycle to enhance Marine Corps learning. The TECOM Future Learning Group's work helps overcome the research–practice gap and more rapidly integrate new capabilities into Marine Corps programs. It also facilitates organizational culture change, encouraging more innovation in Marine Corps training and education—helping the Service move from an Industrial Age model of learning to an Information Age paradigm.

goals: (1) ensure that the messages to the individual communities (e.g., K-12, higher education, employers, military, and government) are in line with their singular goals and (2) that there's a meaningful message that transcends and unites these communities. In particular, we need to be clear that the benefit to both human development as well as to our national development lies in the co-ordination across these communities, that is, in collectively optimizing learning and development. The future learning ecosystem requires that we have a shared, single goal but with an unlimited set of pathways for attaining it.

Compliance and Policy

Individuals in compliance and policy roles need motivation for accepting the future learning ecosystem concept. The stated goal for compliance and policy is often to ensure no problems occur—that is, to mitigate risk. This is especially true in the context of information technology and associated cyber-security and data handling. But to evolve and optimize, risk must be taken. Consequently, we need to work with compliance and policy stakeholders to find the acceptable amount of risk. Who decides that? Who's responsible if a breach occurs? These individuals have experience and knowledge, but are often engaged later in a change process, which creates obstacles to obtaining their buy-in or integrating their ideas into the fledgling system. We need them to give their direct input, be part of the conversations for planning, and help us move smartly towards this new vision of learning.

Implement

Average projects (those not tied to cultural change) usually involves linear planning and straightforward management, with efficiency among their performance goals. However, in an innovation context, where culture change is a necessary criterion, different metrics need to apply. There's a temptation to revert to traditional managerial methods, to emphasize speed, to reward

In terms of transforming the education enterprise, we need strict or serious policy—but not only policy, we also need **resourcing**, **direction**, and **enforcement**. The devil is in the details here because if you were to transform the training and education system into something that is really capabilities-based then the whole flow diagram is going to change. It wouldn't be a block, like the "Class of 2028." Instead, it would be a continuous flow, and you'd have a completely different process. Some may finish slower and present a gap in the pipeline. Others may get completed early and be ready to move on to the next phase. But if the entire system isn't reformed, the next phase won't be ready for them.

James Robb

Rear Admiral, U.S. Navy (Ret.)
President, National Training and Simulation Association

only successful trials, and to backslide into comfortable processes. That will spell disaster for the future learning ecosystem—it cannot function without the genuine buy-in of stakeholders or the radical change of participating organizations.

So, a slower but more deeply rooted approach is needed. Consensus-building working groups, community standardization efforts, and extensive communication will need to support collective implementation planning. This isn't likely to be a speedy process. Leaders will need to balance a reasonable sense of urgency with a considered appreciation of the culture-change process.

Each organization will need its own experiments, incentives, and implementation plans, and these must be devised through collective participation. Similarly, the larger community—possibly at a nation-wide level—needs to coordinate. This may require extensive cross-cutting communities of practice and will certainly mean negotiation of experiments and incentives across domains. Just how this implementation plan is designed and what it will contain isn't yet clear; however, it's apparent that it must serve multiple levels—for the individual stakeholders, their local organizations, and the collective multi-organizational community. And it's also clear that each organization will need to devise its own messages, measures of commitment, and ways of contributing to the larger vision. We are just beginning down this pathway. We have the opportunity to do so "the right way," in concert and with thoughtful coordination; it's important that we resist the urge to speed ahead with shortsighted implementation plans that sacrifice longevity for temporary achievements. "If you want to go fast, go alone; but if you want to go far, go together."[13]

Summary

It's easy to avoid change, to play the cynic, wait out new ideas until the organization returns to the status quo, or find excuses to avoid uncomfortable actions (e.g., remaining in the "analysis paralysis" process). Individuals and bureaucratic organizations, in particular, are often remarkably clever at finding ways to avoid change. It's also tempting to view the future learning ecosystem as simply another technology—as a *thing* that can be installed and activated, and then fueled with educational materials that instructional designers merrily create using more-or-less conventional methods. But this won't suffice. If effective, the future learning ecosystem concept will extensively affect how we each live, work, and learn. It will affect organizational dynamics, societal systems, and maybe even the overall zeitgeist of our time. Such impacts can't be achieved through technology alone. They require coordination, a shared vision, and commitment to it. They require a culture change.

“

...you’ve got to be opportunistic in fixing problems so that you’re not just fixing one but rather fixing multiples. At the same time, you have to try to build and control the narrative; use it as a barometer and take some of the danger out of change. You realize you’ve reached where you need to when people start to give the story back to you. It helps to know that you’ve got a narrative from the beginning that does something that will keep people engaged but will also allow you to implement it later.

Jeffrey Borden, Ed.D.

Executive Director, Inter-Connected Education; Chief Academic Officer, Ucroo Digital Campus; Former Chief Innovation Officer, St. Leo College

CHAPTER 19

STRATEGIC PLANNING

William Peratino, Ph.D., Mitchell Bonnett, Ph.D.,
Dale Carpenter, Yasir Saleem, and Van Brewer, Ph.D.

In this chapter, we explore some of the most immediate steps required to realize the future learning ecosystem across educational, academic, business, government, and military sectors. We discuss the larger system, including people, processes, and technologies, and recommend considerations related to its design, development, and implementation.

Today's Learning Journey

Currently, in the U.S., most children begin formal learning in the conventional education system. Primary and secondary programs follow a fairly linear, time-based model that creates a conservative, general trajectory where children progress through academic milestones more or less as an age-based cohort. Students are largely taught as groups in classrooms and provided with similar lessons and homework. Usually, these curricula focus on key areas of knowledge acquisition to include mathematics, reading and writing, science, and history, often with a few additional areas included such as art, music, physical education, and health. Frequently, development of self-regulated learning capacities as well as social, emotional, and physical competencies aren't formally included, although some students may encounter outstanding teachers or participate in extracurricular activities that foster these abilities.

As students approach postsecondary schooling, more differentiation occurs. They can choose elective classes (although often limited by local availability),

and in some districts, school choice programs offer more diverse options such as magnet, charter, virtual, home, and private schools. Increasingly, students can even opt for fully online high schools, including relatively low-cost national and international programs.[1] Enterprising students, as well as their teachers and mentors, also have access to an increasing wealth of educational resources, which they're exposed to at younger and younger ages, from sources including the National Academies, Khan Academy, TED, and various MOOCs, as well as associated resource repositories such as MERLOT, OER Commons, and Connexions. There's also an unprecedented amount of informal (and sometimes questionable) online resources from YouTube, Wikipedia, and Reddit to countless other blogs, web sites, and apps.

Once students graduate from high school, they can enter the public or private-sector workforce, seek additional vocational training, or matriculate to higher-education institutions. Postsecondary education traditionally involves two- and four-year degree options as well as trade and certificate programs. Colleges and universities also frequently offer advanced degrees in the form of graduate certificates, master's degrees, and doctorates. While many schools still follow traditional methods, the higher-education sector is rapidly evolving with various new choices including competency-based degrees, fully online options, and hybrid programs.

Increasingly, individuals can also acquire credentials outside of a formal higher-education institution; for instance, intensive "bootcamps" have become popular in fields such as software coding, project management, and cybersecurity. We expect this trend to continue and, in the future, we'll see more and more varied credentials—including experience-based credentials earned outside of structured programs. In other words, we anticipate that more programs will be available to accredit individuals for their capabilities and knowledge, regardless of whether they acquired those competencies in formal or informal settings. This will substantially shift the way we view formal learning as well as many related human resources processes (e.g., recruitment and promotion).

It'll change the resumé, too, putting less emphasis on the jobs someone has held or the degrees earned, and more on his or her demonstrated capabilities.

After individuals enter the workforce, their learning journeys continue. They can seek vocational training and additional credentials, attend workshops and seminars, or pursue any number of informal and self-directed learning opportunities. Some companies also offer continuing education or professional development programs for their employees. In the U.S. alone, businesses spend roughly $90 billion annually on corporate training (as of 2018).[2] These offerings range in formality. On the more formal side, there are programs such as McDonald's Hamburger University, the "Harvard of the fast food industry,"[3] which trains more than 7,500 students a year,[4] and Starbucks helps its employees earn first-time bachelor's degrees online through their partnership with Arizona State University.[5] Less formal programs come in many shapes and sizes, including corporate coaching and mentorship, developmental seminars, official and informal feedback, corporate e-learning and webinars, and numerous informal learning approaches. There are abundant resources available, and individuals and organizations have a whole slew of learning and development opportunities to choose from.

A complementary phenomenon to consider is the increased workforce "churn" (the word economists use to refer to people switching jobs). A large, longitudinal study by the Bureau of Labor Statistics found that baby boomers held an average of 11.9 jobs between the ages 18 to 50,[6] and in another report, the Bureau found the median tenure at a given employer, across all ages of wage and salary workers, was only 4.2 years as of January 2018.[7] Many expect to see continued workforce churn in future years, and, increasingly, we also anticipate individuals will have more *careers* across their lifetimes. As the pace of global and technological change continues, jobs will increasingly morph or become obsolete, and individuals at all levels of work will need to engage in additional learning as they progress through their careers. In other words, as discussed in Chapter 4, we'll see increasing, and increasingly necessary,

continuous, lifelong learning—including ongoing up-skilling and re-skilling for workers.

Like the private sector, the public sector and military workforce face similar opportunities and challenges. In general, the same informal learning opportunities exist for these special populations. Agencies throughout the U.S. Government offer wide-ranging learning and development programs, covering the full gamut of formality. For example, the Office of Personnel Management hosts the Federal Executive Institute that provides training in strategic development for senior executives. The National Park Service provides access to a wide range of personal learning opportunities through its internal Common Learning Portal, and the Department of State uses its Virtual Student Federal Service program to provide on-the-job experiential learning opportunities to students around the country. But the U.S. Department of Defense is most notable among these agencies. It's been considered the "greatest training organization of all time"[8] and invests more funds in innovating education and training for its workforce than any organization in history, with the bulk of these efforts focused on programs for its military personnel.

The DoD conducts formal individual, collective, and staff programs, and it actively encourages mentorship, peer-to-peer learning, and self-development. It employs the spectrum of learning modalities including in-resident and computer-aided instruction, simulation-based and embedded training, m-learning, augmented and virtual reality, and hands-on experiential learning. The DoD also has strict education and training requirements tied to assignment and promotion, and particularly for key accession points, it employs several standardized test, such as the *Armed Services Vocational Aptitude Battery* and the *Tailored Adaptive Personality Assessment System*.

Unlike the private sector, service members generally have fairly constrained entry- and exit-points into the military workforce, and almost always, individuals separate from active duty military service before they fully retire from all work. Once service members separate from the military, they may return to

the DoD or federal government as a civilian or contractor or seek employment in another sector. The latter often requires some retraining as well as careful translation of military-centric capabilities into private-sector roles.[9]

BUILDING TOMORROW'S LEARNING JOURNEY

Never before have so many high-quality opportunities for learning existed. Yet, tomorrow's learning environment will be even more advanced as information and communication technologies, automation, and innovation continue to change how we interact, behave, and learn. We have great momentum, but how do we optimize this future system? Towards that end, we've integrated a set of 10 near-term strategic recommendations for the wider future learning ecosystem—drawn from across this book.

1. Bridge existing silos

Public and private school enrollments in the U.S. have steadily risen over the preceding decades.[10] The education, training, and talent development industries are similarly expanding along with corresponding increases in both not-for-profit and open-access resources. However, many of these expansions are happening in isolation. For example, learner records are typically housed in stovepiped data silos. Someone might spend 13 years in school as a child and then graduate with a high school diploma and a transcript with letter grades. Any additional specialties, sub-competencies, extracurricular activities, or other insights are usually absent from this documentation. The same is true of the university or vocational school outputs, and, typically, for previous work experiences, which may be documented (say, on a resumé) but are rarely assimilated as meaningful data. A similar story happens throughout service

members' and civil servants' careers—there's lack of robust data as well as a lack of permeability of data between formal and informal learning, and among academic, business, and government institutions.

The future learning ecosystem will enable an environment where the different tools, technologies, and systems a person encounters can communicate data about his or her performance and the contributions of different activities to it. Key to this vision, the various systems will need to interoperate, collect and share meaningful data, and use that compiled information to promote tailored instruction. In other words, we'll need greater interoperability across learning systems and, correspondingly, greater portability of learning-related data. Part of the change will also likely involve creating systems of learner-owned and managed data that use metadata to ensure authenticity, respect learners' privacy needs, and broker across different systems. This will require a unique set of capabilities to accommodate security, privacy, architecture, and content, and it will place demands on development, deployment, employment, and assessment of learning systems. This technological architecture for learning forms the essential backbone of the future learning ecosystem—connectivity across time and space make the entire vision possible—hence why interoperability, data specifications, and learner-centric universal profiles top our recommendations list.

A **universal learning profile** will act as an external repository where individuals can hold their data and share it as desired to drive educational choices, personalization, employment eligibility, and personal growth.

2. Foster full-spectrum competencies

Increasingly, schools and employers are recognizing the impact of social, emotional, metacognitive (self-regulatory), and physical development. While these competencies have always been important, there's greater recognition of

Key Take-Aways

1 Bridge existing silos
- Enable system interoperability and data sharing
- Develop learner-owned universal learner profiles
- Research questions of security, privacy, architecture, and content-sharing

2 Foster full-spectrum competencies
- Integrate social, emotional, metacognitive, and physical development
- Apply asset models (versus norm-referenced developmental models)
- Use personalized interventions across the developmental dimensions

3 Reveal and enable informal learning
- Acknowledge and integrate informal learning
- Foster individuals' self-regulated learning capabilities
- Make it easier for groups to engage in social learning

4 Improve assessment
- Limit high-stakes summative assessments, particularly in K–12
- Integrate more formative, portfolio-based, and experiential assessments
- Make assessment data and feedback visible to learners

5 Up-skill and empower learning professionals
- Help learning professionals develop the new capabilities they need
- Reevaluate the organization of learning professionals; focus on teams
- Define and support the development of learning engineers

6 Plan for integration across learning and personnel functions
- More tightly integrate training and education with talent management
- Update organizational systems to better accommodate informal learning
- Consider up-skilling and re-skilling programs

7 Facilitate a mindset shift
- From cognitive and teacher-centric to holistic and learner-centric systems
- From linear and time-based to personalized and nonlinear
- From isolated to more interconnected learning systems

8 Enable learning at scale, technologically and methodologically
- Build extensible, open-architecture components
- Research methods that support interconnected, lifelong learning
- Consider changes across the social and organizational structures

9 Design for convenience and equity of access
- Make UI/UX considerations paramount
- Ensure all learners have sufficient connectivity and access to technology
- Carefully consider the social implications of the learning ecosystem

10 Ensure laws, policies, and governance keep pace
- Evaluate (and update) formal laws and policies
- Encourage participation in cross-cutting professional organizations
- Develop cross-cutting working groups and governance processes

their impact on life-long functioning and as a result, motivation to more actively and intentionally support their development. Developing these "full-spectrum" competencies must begin at the earliest opportunities and should also continue throughout our lives, because as individuals grow they'll encounter new challenges that will continue to test their holistic capabilities and require personal strategies to navigate effectively.

It's necessary to begin with the foundational years (kindergarten through 8th grade), to widen the curriculum focus to include social, emotional, metacognitive, and physical development as part of formal education. Creating objectives for teachers in these areas provides the policy justification they need to spend time in the classroom explicitly focused on developing the whole student. Inclusion of these competencies, however, necessitates a shift to an asset model of growth, which places more emphasis on what students can do currently and what they need to learn next—as opposed to focusing on areas where improvement is needed to meet norm-referenced or "typical development" milestones. This shift from achievement-orientation to growth-orientation can also improve motivation to learn and promote lifelong interest in self-driven learning.

In the secondary and post-secondary institutions, we should continue to integrate these competencies into the more traditional curricula, while still recognizing that individuals grow and mature at different rates. In other words, the asset-model of development will need to continue into early-adult and adult education, which will create a greater need for personalized education as the range of individuals' potential capabilities widens.

In workplace settings, too, we anticipate employers will increasingly value and seek to hire for "full-spectrum" competencies, hence developing and measuring them throughout adulthood will grow ever more critical. However, developing these competencies and assessing their current levels within each person is challenging, particularly in the less-controlled post-secondary and workforce settings. Consequently, it'll be necessary to better leverage and

be able to measure the impacts of informal and nonformal learning on these outcomes. Data that meaningfully capture these experiences, as well as the interests and noncognitive abilities (social, emotional, and physical) individuals demonstrate in these settings, can help inform these assessments as well as drive future learning and development opportunities, encourage learners' motivation for self-regulatory learning, and help stitch together learning across separate episodes. Among other things, this will also require "lifting the veil" between workplace and learning-place settings, allowing closer integration between learning and performance (or operational) venues.

3. Reveal and enable informal learning

The future learning ecosystem moves us toward a holistic approach to learning that connects the various "above ground" and "below ground" learning structures, processes, and systems.

In learning and development circles, there's a popular notion called the 70:20:10 model.[11] It estimates that around 70% of learning is informal or on-the-job, about 20% involves peer and social learning, and only about 10% is formal training and education. While this model is merely a general concept, not a firm quantitative rule, it helps underscore the importance of surfacing informal learning—i.e., the 90% of learning that occurs outside of formal settings. Informal learning is pervasive and interwoven into the fabric of our professional, academic and personal lives, and we must be able to reveal and understand this complex set of behaviors to achieve the goal of holistic, life-long learning.

As we progress to a more chaotic and data-saturated world, self-regulated learning skills, or the ability monitor and motivate oneself in learning, will become even more important. Accordingly, learning in the future will not only rely on one's ability to learn provided material but rather the ability to seek

When you take away the performance aspect, people act differently. In "practice" settings they're freer to make mistakes without someone reviewing and judging them. When they're being assessed, though, people bring to bear a different mindset and focus. If we replace more traditional assessment with "stealth" assessment, will we introduce a paradigm that's counter to a growth mindsets and to how learning happens best? If they have to be always "on" that could be a really challenging dynamic for our learners.

Michelle Barrett, Ph.D.
Vice President of Research Technology, Data Science, and Analytics, ACT

out new information, determine its accuracy and relevance, and assimilate it in a manner accessible and translatable to the real world. We will need to educate and empower people to distinguish accurate from falsified data, manage data saturation and information overload, and cultivate persistent energy for lifelong learning. However, individuals' abilities to engage in *effective* informal learning vary. Hence, it's important to foster individuals' self-regulation capabilities and facilitate their active engagement in self-directed learning, for instance, by providing access to resources, making learning content more easily "findable" (such as via metadata), or encouraging learning through personalized prompts.

Of the various informal learning modalities, social learning seems to be particularly poignant, as well as practically supportable. It's all about collaboration—bringing in some of the social aspects that enable individuals to share and learn from each other. Enabling collaboration, the sharing of information,

and co-creation of ideas are important, whether in professional or academic settings, and not all interactions need to be formally organized. Side conversations at the water cooler and informal feedback have surprisingly significant impacts on how work is accomplished.

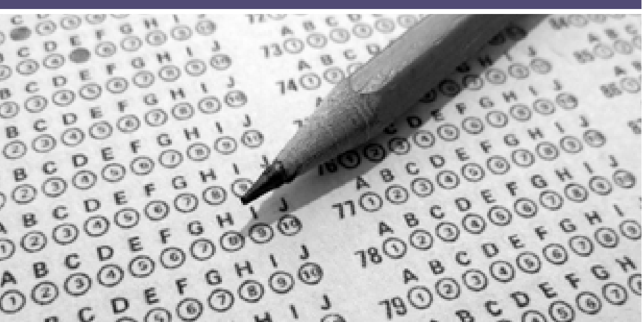
Already, many commercial vendors are developing solutions to support and integrate such informal opportunities. The learning and development industry also seeks to gather related analytics that can help provide learners with personal, relevant, and engaging social learning experiences. Nonetheless, many research questions remain that the scientific community still needs to address, including maturing our understanding of how to develop individuals' self-regulated learning capabilities, how to best support informal learning in applied organizational contexts, and how to quantify the range of formal-to-informal learning.

4. Improve assessment

Assessments, along with the learning data they generate and evaluations they enable, play foundational roles in training and education. In the future, with the increased emphasis on personalization and data-driven systems, assessments will only grow in importance. However, the nature of the assessments will change.

At the K–12 level, the number and use of standardized assessments currently poses several challenges to learning. Today, in the U.S. system, students are required to take numerous standardized tests; the results from these are used to identify struggling students or, in aggregate, to uncover underperforming school systems. In both cases, the assessments serve as accountability devices. Once a child or school is shown wanting, more assessments are used to focus and monitor their remediation. While this sounds logical, in practice, time spent on such detailed work can be emotionally and cognitively taxing as well as a drain on overall learning time. Emphasis on such high-stakes

> The problem is, with all the assessments we have to bombard students with, we don't have time to do the project-based work. That, in and of itself, is defeating. Teachers have the lessons, but they don't have the time to develop them with the students because of all the testing.
>
> **Sandra Maldonado-Ross**
> President, Seminole Education Association (Florida)



summative testing has been shown to shift the focus away from true learning and instead to encourage superficial "teaching to the test"—tests that typically emphasize cognitive abilities to the exclusion of the "full-spectrum" competencies described above.[12]

In the future, assessments for secondary and postsecondary education need to focus on feedback and "feed forward" support—across all developmental dimensions. To the extent possible, and with balance so that individuals aren't continuously being monitored, a rhythm of automatic assessments in forms more closely resembling integrated formative assessments, stealth assessments, portfolio evaluations, and experiential trials should be considered. Hence, significant attention needs to be paid to understanding new ways to prove capabilities beyond the current forms of assessments, articulation of grades, or standardized testing methods. Our concepts of assessment also need to expand in scope. For instance, assessments of large-scale outcomes, such as mission success and task accomplishment, can provide significant, valid data for determining competency. Such organizational assessments, however, must be linked to the learning institutions that can foster such performance or respond to gaps in it. We can no longer consider assessments of learning and performance as sequential, causal, chronological occurrences; rather, both become inextricably linked and interdependent.

The relationship between assessment, feedback, and self-driven learning is particularly meaningful to consider. To better enable self-regulated learning, individuals, groups, and organizations need access to their data, both at the discrete level (e.g., data from one assessment) and in aggregate (e.g., across learning arcs). Such data can inform better learning and development choices—but they don't guarantee it. Data alone aren't enough; data need to be presented in ways that support decision-making. However, large volumes of data can create complexity and overload, making them undigestible and less useful, and "noise" can enter the system, reducing the clarity or true meaning of the data. Hence, tools are needed to help individuals turn data into insights and actions. Accordingly, big data analyses and accompanying visualizations are needed to help learners, learning facilitators, and learning organizations navigate modern learning systems.

5. Up-skill and empower learning professionals

As learning contexts evolve, so too do the roles and requirements for learning professionals within them, notably teachers, trainers, educational technologists, and instructional designers. The speed of progress in this sector means they'll need to learn continuously—keeping abreast of the latest research, technologies, and regulations. Ongoing professional development to re-skill and up-skill learning professionals, using formal and informal methods across diverse media, will be critical.

Learning professionals will also need new teamwork skills. Historically, someone could be a great teacher in an isolated classroom, without requiring the support of other learning professionals. In the future, teams of specialists—each with unique areas of expertise—will be required. Pedagogues will need to work with data scientists; AI developers will need to collaborate with media designers; and human resource specialists will need to coordinate with education and training leaders. At a personal level, individuals will need to

develop appropriate collaborative skills, and organizationally, new administrative structures may be needed. For instance, instead of assigning a single teacher to design, develop, and implement a course, a composite team may be required. Some of these individuals may reside within a centralized "pool" of shared talent (say, for the data analysts), while others may be dedicated to the given program (for instance, the main teacher). Holistic solutions will include cross-training talent management professionals, institutional administrators and operational supervisors—all of the 70/20/10 components of learning.

The future learning ecosystem will likely be a highly technical and collaborative environment supporting both micro- and macro-level instructional strategies, maybe even leveraging the "in-between" learning experiences and events—between classes, courses, and life events—to adapt to learners' interests, needs, prior knowledge, and resources. As we begin to look at learning across the lifetime, leveraging big learning data and new learning strategies, learning professionals will need new knowledge and skills. This has driven efforts to define the concept of a learning engineer (see Chapter 16), to close the gaps between technology and instructional design, and between isolated instructional events and larger-scale learning systems. We'll need new conceptual models that define learning engineering, their professional practices, certification and skills, professional development processes, and integration into teams and organizations.

6. Plan for integration across learning and personnel functions

The future learning ecosystem vision views learning as an integral and ongoing aspect of life, woven throughout work and personal contexts. This has unique implications for employers, who will no doubt leverage it as a *learning and performance ecosystem* that "enhances individual and organizational effectiveness by connecting people and supporting them with a broad range of

I just did a survey on issues for teachers asking them what their biggest issues in the classrooms are. Four major issues in the survey were found.

First, academic freedom doesn't exist anymore: "Learn as you live is gone."

Some of the other big issues were about the evaluations. They pressure teachers and administrators. In any other job, you're evaluated on what's seen, but people don't go into surgeries and second guess everything the surgeon does. That doesn't happen in a regular job; they don't get an evaluation that nitpicks every possible thing they do to ensure it fits into the rules of what they're told is important. The administrators, many of them don't like how strenuous and stressful the process is.

The third was stress in the classroom and stress in the working conditions. If there isn't strong contract language then when there's an issue it's tough to fix.

Finally, there are professional development trainings. Education is changing so quickly, but how are you expecting me to go to professional development training on top of 60 hours of working? If you don't go to the trainings, you can't learn what new stuff is available, but if you do go, then you're missing the classroom work.

Sue Carson

President, Seminole Education Association (Florida)

content, processes, and technologies to drive performance." [13] In other words, we imagine employers will seek to leverage it for their talent management, performance support, knowledge management, access to experts, social networking and collaboration, and structured learning functions.

From these components, organizations can craft an infinite number of dynamic solutions for developing and employing individuals, and for optimizing their institutions, writ large. For instance, organizations will be able to better select and place individuals, shifting away from gross measures of someone's capacity (such as a degree title) and towards competency composites. Psychological and behavioral analytical data will aid developmental recommendations, identification of talent, and connection across employers and educational experiences. Those same data can be used to improve task assignments or encourage higher rates of retention.

Organizational processes will, therefore, need to evolve to support greater multidirectional integration among training, education, human resources, and talent management systems. The Federal Human Capital Business Reference Model could be used as a guide. This model was developed jointly as a public-private partnership mixing human resources, policy, and industry experts to create a streamlined and simplified HR system. The model denotes functions, sub-functions, authority, and policy. It also clarifies the Human Capital Management lifecycle government-wide. Ultimately, this model directly informs how HR practitioners plan for, work with, and organize people, policy, process, service delivery, and data categorization and reporting.[14]

In the future, we expect to see greater churn across roles, companies, and careers. As workers increasingly value flexibility, fluid work/life structures, and personal experiences, we may also see more "gig economy" careers, where individuals or teams are available for project-based work or consulting services but don't work directly for a single company. Correspondingly, there may need to be greater permeability across the workforce, encouraging people to move into and out of formal learning, full-time jobs, and personal developmental ex-

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> If we’re going to align learning with employer needs, we need to deal with job descriptions and postings, and how they’re organized on the web. Advancements in data standards now allow us to create structured, dynamic data on the web. Thus our goal is to: 1. Extend and improve data schemas for jobs, and 2. Link it to the web semantically. Structured, linked data maximizes our ability to search, discover, and compare data about jobs, and to notify anyone instantly when a job has changed and in what way. By organizing jobs-data in this way, we can create an entirely new labor market information system, directly from the hiring systems employers use.
>
> **Jason Tyszko**
>
> VP, Center for Education and Workforce, U.S. Chamber of Commerce

periences. Continuous up-skilling and re-skilling of the workforce will become paramount. Taken together, this implies individuals’ competencies will likely need to constantly evolve, meaning someone skilled at learning will be highly prized, and organizations will need to better accommodate a variety of lifelong learning mechanisms notably nonlinear, informal, and nonformal learning options. We may also need new social paradigms, for example, for things like re-employment insurance that can be used to fill the gaps between careers.

7. Facilitate a mindset shift

The success of the future learning ecosystem concept is, in large part, predicated on culture change. A significant mindset shift will need to accompany any advancement from the Industrial Age of learning towards the future learn-

> I think the challenge for the Department of Defense is that we're using the same outlooks and perspectives that we've been using since 1947. The Department has to change its thinking. My own personal answer to that is borne out through my work on the *Force of the Future* reports; the only way you're going to change how the Department thinks is to bring in people who look different. It's fundamental; we need to increase the intellectual diversity of the Department.
>
> **Morgan Plummer**
> Director, MD5 National Security Technology Accelerator
> U.S. Department of Defense

ing ecosystem vision. Incremental changes or mere additions to the current system won't suffice; stakeholders, which includes nearly everyone in our society, need to willing embrace the new paradigm.

We need to change how we typically perceive education and training. Very broadly speaking, today's systems tend to emphasize formal learning. Individuals largely progress through prescriptive and similar paths, most commonly based on time factors. Courses (including technology-based offerings) are often authority- or instructor-centric; learners' roles are to receive the experts' knowledge and then engage in predefined practice activities. In the future, we must be willing to embrace more flexible and personalized outcome-focused learning that happens across diverse places, time, and modalities.

We also need to shift our perceptions of teachers and trainers, from the sources of learning to its facilitators, and in turn, more genuinely emphasize learner-centric methods. For instance, beginning with primary education, this mindset shift might mean transforming formal education spaces from places where students receive information to places where they co-create it. In the secondary school years, students might take greater control of their own learning journeys, which may mean more lenient rules for required courses and greater encouragement for self-directed learning.

Closely related, we'll need to embrace mastery learning and nonlinear, tailored learning. While such concepts have been touted for decades, most systems—whether formal schools or workplace development programs—still tend to emphasize time factors and minimum achievement standards. To move ahead, we'll need to let go of the idea of "minimally acceptable" as an advancement criterion. Similarly, we'll need to allow more flexibility in systems, moving away from amassed education and training approaches, with predefined linear curricula, and instead towards more nonlinear, personalized trajectories.

Finally, we'll need to change how we approach the "ownership" of learning. Today, we have separate silos of learning and separate "owners" of those silos—who usually also claim ownership of the data within them. The future learning ecosystem represents a dramatic shift away from a single organization trying to meet all education and training needs with a top-down design. In the future, separate entities will need to negotiate within a shared "marketplace" of learning that has no single owner, leverages the power of self-discovery by placing tools into learners' hands, and relies on integration across a system-of-systems. Without careful plans, we may find increased separation and artificial "walls" between segments of the ecosystem, as different commercial vendors or learning institutions try to sell proprietary solutions or promote systems that are intentionally cumbersome to export data or move away from, so called "vendor lock." Changing mindsets (and incentives) to embrace this new model may prove challenging, both for individuals and organizations.

8. Enable learning at scale, technologically and methodologically

To make the learning ecosystem practical, particularly from a resource perspective, it will need to support a large number of learners and organizations. Similarly, it will need to be future-proofed: designed to meet today's

> When I got a job here, I wanted to change people's minds about math. I could do it in the dozens or maybe hundreds. Now, educators are more empowered because it's not just who they can teach in the classroom—now they can reach thousands.
>
> **Ralucca Gera, Ph.D.**
> Associate Provost for Graduate Education and Professor of Mathematics
> Naval Postgraduate School

requirements but also with a structure that can evolve to meet future needs and advancements. Technologically, such a complex system can't be built from a single blueprint; it can only be achieved through an open systems architecture approach. This necessarily emphasizes interoperability, modular designs, common technical specifications, shared data standards, and negotiated data rights as well as extensibility in all components to help grow the system over time. A long-term strategy, including broad community coordination for training and education technologies, data and metadata policies, and collective technical governance, is needed. Paradoxically, this learning at scale will accompany an increase in the intimacy of learning, as the same technology that enables access also increasingly supports the "mass customization" of tailored, personal experiences.

Similarly, various social and organizational structures will need to be reconceptualized, as these changes in learning will create wide-ranging impacts, from the way our K–12 schools function to the nature of work across society. For instance, the timing for students attending school may change; the movement into and out of employment organizations may change and grow in frequency. Widening the aperture and access to learning might also change the nature of traditional trade schools and colleges, and it will likely create new markets for different educational experiences. For example, new entities may appear in this learning market to provide "credit" to "students" who take part in experiences, ranging from something like rock climbing and travel

excursions to bootcamps and competency-based micro-degrees.

From a methodical standpoint, there's an imperative to conduct deliberate investigations across the range of new learning approaches, including those outside the dominant paradigm. For example, how do contextual factors, including culture, social context, instruction, and time of life, impact learning?[15] How does technology influence the psychology of learners, and what are the design requirements for nonlinear lifelong learning? How can learners aggregate and make sense of learning across multiple experiences, while minimizing cognitive friction? There's much to consider. Our models of learning and teaching must evolve, both in theory and practice, and be translated into reference sets, use cases, and other formal representations to inform the design and delivery of learning at scale. To support that, however, we first need the technological backbone and the mindset shift. These questions can't be answered within the current system because it impedes access to, integration of, and sufficient measurement of learning—all of which are necessary for addressing these questions. Thus, the only option is to create a system-of-systems approach that supports its own continuous evolution.

Once realized, the technological architecture doesn't just allow for improved access to status-quo learning opportunities—it creates an entirely new capability. Metaphorically, consider the components of a car (the steering wheel, tires, pistons, and so on); separately, they're functional objects, but when connected together, they can produce an entirely new capability—*transportation*. Similarly, the future learning ecosystem, by the aggregate nature of the systems that comprise it, will create unimaginable new capacities, more than merely the sum of its parts or the incremental expansion of today's learning paradigm.

9. Design for convenience and equity of access

Usability is often the limiting factor of technical systems. No matter how brilliant a new application or hardware solution, if real people in real-world

Example

There are 417 national parks and monuments. We're all over the globe. We're in remote locations. You can lose your cell service. It says on our website that we had 340,000 volunteers in 2016. How do we train all those people? We don't have any subject-matter experts in our Washington office—the expertise is out in the parks. How do we get that knowledge into our system and then out to the workforce?

We created the Common Learning Portal. It's a web portal—a marketplace for training. It opens April 2019. The government's cybersecurity processes (FedRAMP) kept us from opening the doors sooner; it's been in pilot-project mode, but operational, for two years now. It provides a comprehensive learning performance ecosystem, a holistic view of learning. The system enables us to put information, people, and other learning resources in places where people can find them, even on a mobile device. We hope our personnel and volunteers who have been out in the field for work can go back to their offices and do their training, which they have to do at the beginning of every cycle. Already, we have over 500,000 page views and 4,000 registered users—without even formally launching. It's caught on by word of mouth. Some trainers got excited. We had support from leadership and people. It was a grassroots effort.

So that's where we are going tomorrow. We're not throwing away formal learning, but we're trying to pull in performance support, microlearning, and things that allow us to better do our jobs.

Courtesy of Dale Carpenter

Superintendent (Acting), National Park Services

contexts can't use it, it won't achieve its goals. At this most obvious level, this means system usability—across its various user interfaces and user experiences—plays a major role in its success. It's necessary to put a focus on UI/UX, making all aspects of the system as intuitive, modern, and effective as possible, to increase adoption and facilitate its customization to unique requirements across the broad stakeholder community.

Similarly, issues of network connectivity and technical access are equally important and extend beyond technology, touching on social and societal considerations. Access issues already limit educational opportunities for children in many rural or underserved areas. As more of our learning becomes digitized and networked, we must carefully ensure equity in access to it—not only for ethical reasons but also to maximize the diverse capabilities of society and enable all to realize their unique potentials. If not, we risk widening the education gap, creating greater disparity in access to quality education and training, and potentially creating a bifurcation between the "haves" and the "have-nots." In other words, we could inadvertently build a divide between those with access to open, unstructured junk information versus those with access to higher-fidelity, semi-automated methods of transmitting quality knowledge within and across communities.

The advent of the learning ecosystem could affect populations, workforces, wealth distribution and other social factors. Until such time that the ability to adapt to the pace of change becomes irrelevant, adaptation will become increasingly ever more important, and that will rest squarely upon the ability to learn. We must carefully consider not only the social implications of establishing the learning ecosystem but also its impact on those unable to fully benefit from it. We have an ethical imperative to consider if, and how, access to learning is protected and enabled throughout society—and perhaps even across the globe. If managed effectively, however, "education for humanity" becomes a real possibility, bringing knowledge and elevating the capabilities of our entire world.

10. Ensure laws, policies, and governance keep pace

Holistic solutions will demand holistic governance, as well as new law and policies. These may span broad areas of consideration from technical frameworks and interoperability standards to content and data exchange processes, and equity, ethics, and fairness of use. Below are a few considerations, but this discussion will require a much more extensive treatment, as well as interorganizational coordination, to fully outline.

Starting with K–12 education, new policies and processes are needed in several areas. For example, moving to competency-based learning methods will be key for fostering a learner-centered, development-oriented system. In the U.S., the *Common Core Standards*, in theory, allow for a similar kind of coordination. In practice, however, these standards have become inflexible requirements added to already overloaded schedules. Transitioning to a competency-based model would better allow teachers to personalize learning and let students earn credit for knowledge acquired outside the classroom. Teachers will need policy to support them in exercising the academic freedom required by this model, to be able to adjust content and methods to meet each student's unique developmental needs. Additionally, as indicated above, competency goals will need to be augmented to incorporate social, emotional, metacognitive, and physical elements for "whole person" development. Additionally, the *Every Student Succeeds Act* focuses on providing funds to schools that use evidence-based practices, yet teachers and administrators rarely receive formal training on research design and statistics. Expanding existing governmental programs (e.g., the Education Innovation Programs, U.S. Department of Education) that aid in closing this research-practice gap will help optimize learning and can also support the up-skill and re-skilling of learning professionals (as described in Recommendation 5, above).

For post-secondary and workforce education, policies must address key cross-community issues, including funding allocation, data sharing, and data

The big thing here, that everyone's dealing with, is the challenge of: **How do you transition into a performance organization**? How do you support an organization trying to become a performance-based one, and what are the other things that wrap around that structure? For example, talent management systems are important, but the way HR people manage now is mainly through "box-checking," like the things that you're required to do for mandatory training. We'll have to rework so many things—HR, the compliance stuff, and assignment decisions…Conceptually, though, it's always been the same thing: How do you choose the right people?

Michael Freeman
Consultant, Training and Learning Technologies

usage rights. The diversity of learning venues obviates any unitary solution, but certain characteristics will be common, such as privacy, continual assessment, and security.

As we progress to a digitized nation, we will need to ensure ethical use of learning data, both for students and employees. As such, policy must be written that ensures individuals can own their own data, with updated laws designed to protect them in current and evolving contexts. Existing laws, such as the *Family Educational Rights and Privacy Act*, provide some measure of protection, but weren't designed for the kinds of data-rich, technology-enabled learning that's emerging. They also tend to focus on the education "silo" rather than a lifelong perspective. A balance across stakeholders, notably between the public and private sectors, will be needed, particularly given the commercial value of data as a sharable resource. Such laws and policies need

We know we have a shortage of talent (human capital) for certain positions but we can't just "up" our recruiting tactics.…We've got to transform how we put them into that pipeline. The big thing I want is to integrate government with industry and universities—to formalize partnerships sooner, so we can get smarter about what people need to be ready to participate in our workforce. Right now, the people we need aren't coming out of the universities; so, we've got incentive to work together. We could start small with a representative government agency that could be our champion and also couch the program as a college internship or co-op. We have to figure this problem out—we have to grow our workforce.

Anne Little, Ph.D.
Vice President, Training Solutions Development, SAIC

to be reconsidered for the future context and designed in a way that balances privacy with functionality.

New policy considerations will likely also concern accreditation standards and assessment validation. For example, consider a medical student who's gained competencies through means other than formal education (e.g., an internship as a teenager, combined with lifeguard training, volunteering as a medic for local disasters, and online personal study). She could, in theory, graduate from medical school earlier than her peers—however, only if valid assessments can be used to comprehensively evaluate her capabilities across the full-spectrum of necessary competencies. Beyond developing such assess-

ments (as mentioned in Recommendation 4), who will validate them, update them, and accredit their use across learning and workforce systems? Further, how will schools that provide degrees based on mixed methods for competency attainment be formally accredited or ranked? To continue our example, laws involving medical insurance, malpractice determinations, and formal licensure might be impacted.

Broadly, there's also a need to develop interoperability specifications. Professional organizations, such as the IEEE Learning Technology Standards Committee or ISO IT for Learning, Education and Training, help formalize technical standards across communities. However, this still only applies to the interface or data layers. Each organization still makes many independent decisions about instructional media, new technologies, and their technical and programmatic factors. While organizations should retain their autonomy, there's opportunity to increase coordination, give collective guidance, and at least within organizations or alliances, to create shared processes. A federated data system is an extensive endeavor. We have to constantly ask, how can we protect this system and yet keep information as open as possible? Thus, additional governing agreements in the areas of cybersecurity, privacy, and identity, as well as considerations for copyrights and data ownership, are important. For example, for the U.S. Department of Defense *DoD Instruction 1322.26 ("Distributed Learning")* provides guidance on best practices for distributed learning and permissions to collect, aggregate, and assess data. This is one of many policies that could be reviewed to encourage greater unity of action across the military services and other defense components as well as the U.S. Government, writ large.

We need to develop effective forms of governance for a diverse and disparate community of practice including government, academic, and industry partners. This macro concern for governance is a mirror of what must occur within the future learning ecosystem, itself: As components federate to attain a capability the need for agile partnerships will grow, enabling rapid aggrega-

tion (or disaggregation) of federated capabilities. Such collective governance will need to set approaches, policies, and management strategies that education and training stakeholders can adopt to enable effective learning—not only within a given silo—but across the composite, collective system.

Finally, there is a broader imperative that frames our approaches—policy and methodology—for moving towards the future learning ecosystem. We do not, and cannot, fully appreciate the impacts of exponential technological change, particularly as we approach the point beyond which it's impossible to fathom (the "singularity"). Ethical considerations must be an innate characteristic of our process methodologies, or we will sacrifice the human nature of progress. Simultaneously, our span of regard will grow to include machine learning as an essential and constant complement to human learning and employment; areas that we cannot approach reductively. Consequently, process perspectives and non-linear contexts will characterize the evolution of the future learning ecosystem—perhaps the final step away from Industrial Age thinking.

CONCLUSION

In this chapter, we've offered several recommendations for the advancement of learning. Throughout this process, we've assumed that technologies, notably automation and data analytics, will continue to advance. In other words, we felt it safe to assume that such capabilities are (or would be) technologically feasible. The challenge lies not in developing the technologies but in their validation, effective integration into learning systems, and consideration for the corresponding social, organizational, and societal changes they'll produce.

It's not feasible, nor frankly advisable, though to plan out every piece of this future learning ecosystem; the rapid pace of change and its complexity necessarily require its design to be dynamic, flexible, and collaborative. However, we've attempted to apply systems-thinking approaches to the planning pro-

cess, considering the comprehensive "talent development system," including formal and informal training and education. We've also tried to harmonize across the principles of learning science, learning technology, data science, organizational dynamics, and policy, and consider a lifelong learning continuum to include K–16, the public and private workforce, military service, and self-directed learning. Specific solutions should be grounded within this larger tapestry so that when implemented, they're most likely to work in concert across technology, design, commitment, governance, policy, and human infrastructure factors.

The immediate and enduring relevance of this discussion is clear; we're conducting basic research now that will provide knowledge to reframe our future paradigms, bounding the unknowable to both enable and constrain future choices. We recognize whatever choices we make will have consequences, but learning, itself, is essential for making those future choices. The confluence of learning and technology—the evolution from traditional schools, to distributed learning, and now to "ubiquitous learning"—is driving us towards the need for learning across time, space, and function using tools and techniques from across diverse venues to enable seamless lifelong learning, whether training, education, or experience, as part of a holistic approach to empowering human potential. Interdisciplinary stewardship will be essential to extend and connect learning science, policy, and technology to address today's challenges and be prepared for the unknowable future.

> If we don't like the rules,
> why don't we **change the rules**?
>
> – **Reese Madsen**, Senior Advisor for Talent Development, U.S. OPM
> Chief Learning Officer, OSD (Intelligence and Security)

End Matter

ENDNOTES FOR SECTION 1 (FOUNDATIONS)

Chapter 1 Endnotes

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Chapter 9 Endnotes

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